WHEN AND WHERE: SPATIOTEMPORAL ANALYSIS OF DYNAMIC PUBLIC TRANSIT ACCESSIBILITY ALONG THE WASATCH FRONT

by

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STATEMENT OF THESIS APPROVAL

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ABSTRACT

The literature is rich with studies about accessibility to opportunities. However, most of these studies focus on driving or assume a fixed transit travel time between origins and destinations. Using the Utah Transit Authority's (UTA) public transit network, this research uses temporally dynamic public transit travel times in an effort to explore spatiotemporal variability in accessibility. We make use of new tools to transform freely available General Transit Feed Specification (GTFS) data into a routable Esri Network Dataset (ND). This research examines how accessibility provided by public transit fluctuates through the estimation of minute-by-minute transit travel times between all census block groups (CBGs) in the Wasatch Front. In addition, because research has shown that different social groups travel at different times of the day and for different purposes (work, school, health care, etc.), this research examines how fluctuations in accessibility differentially affect the transit-dependent population. As a result, we will depict how social inequality in transit provision can be viewed through both spatial and temporal lenses.

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EXECUTIVE SUMMARY

In Transportation Geography, the study of *accessibility* is of vast importance. In contemporary literature, accessibility has been loosely defined as a measure of "the ease with which people can reach their opportunities or services," including health services, affordable food locations, and employment opportunities (Lei, 2010). Public transportation has been one of the modes where accessibility has been extensively studied, mostly due to the fact that different social groups in the population rely on public transportation in different ways (such as the affluent individuals using private automobiles and the less affluent relying more heavily on public transportation).

Numerous studies have also been performed to perfect measuring public transit accessibility. An examination of these previous methods has shown that some are too simplistic, especially those that only performed buffer analyses around transit stops. In addition, the more advanced studies that did take into account transit schedules and ingress/egress walking times only examined the transit network at static times of the day (such as AM/PM rush hour) and therefore extrapolate that all of the social groups are provided the same level of service. However, research has shown that different social groups within a population travel at different times of the day and therefore have different travel demands.

Since a preliminary review of the Utah Transit Authority's (UTA) transit schedule showed that there is variation in service throughout the day, it was important to gauge whether or not UTA services provide adequate equal access from all origins to all destinations for the whole population across an entire day and not just at one particular fixed time segment, such as 6am to 9am. The purpose of this research project was to formulate an accurate method for calculating and determining if and how public transportation accessibility varies during a normal weekday, Saturday, and Sunday along the Wasatch Front and if and how this might result in social inequality in the population.

The foundation of this research revolved around the use of the freely available General Transit Feed Specification (GTFS) data that can easily be downloaded via the GTFS Data Exchange website. These data contain text files that together provide an overall view of when and where the transit network provides service. Demographic data from the Census Bureau were also used to examine transit service equality to different types of destinations. Lastly, to provide a more detailed look at equality, travel surveys that contain actual trip details (including origin/destination, time, and demographic data of the individual) were analyzed.

All of the analyses that examined the performance of service to certain destinations, as well as the social equality aspect were dependent on the creation of a complex 3D matrix of travel times. Each entry in this public transit travel time cube (commonly referred to throughout the rest of this paper solely as cube) was the fastest amount of time it would take to get from a particular origin to a particular destination (which for this study were all of the Census Block Group centroids within 3 miles of the transit network) using public transit. This cube was then sliced into smaller, more manageable subsections in order to explore the usefulness of the cube by performing some novel analyses. These analyses included examining how public transit travel times vary across the entire Wasatch Front, how distance plays a factor on public transit travel times, how service and demographic equality can be explored to certain destinations, as well as between specific origins/destinations (OD), and lastly how the cube can be combined with other data sources, such as travel surveys, to gain a better understanding of how well a transit network provides equal service to different demographic groups based on their travel demands.

When examining public transit service across the entire study area by exploring travel times and travel speeds, it was shown that the center of the valley is provided faster travel times compared to the northern and southern reaches of the valley. However, when examining speeds, the opposite was seen, with the center of the valley having slower travel speeds (due to the reliance on the slower modes of transit: TRAX light rail and local bus) while the northern and southern reaches enjoyed the benefit of faster travel speeds (due to access to FrontRunner commuter rail, which is the fastest mode on the network).

As would be expected, as distance between origin/destination pairs increased, so too did the travel time. However, the results indicated that travel times are anisotropic in the study area, with those that use transit to get to locations mainly north or south of where they live having lower travel times and higher travel speeds than those that travel east-west or west-east, especially the Hispanic or non-White populations.

The travel time, travel time range, and travel speed analyses from all of the origins to specific destinations also showed some interesting findings. For travel time, the results indicate that overall, service begins the earliest on a weekday and latest on Sunday. By contrast, service ends the earliest on Sunday and ends the latest on Saturday.

Overall, the results for travel time ranges indicate that the low ranges of travel times and, therefore, more consistent service occurs mostly in the morning and late afternoon. Also, the higher ranges of travel times and therefore more inconsistent service occurs late morning or early afternoon. Lastly, for travel speed, similar patterns were shown between each of the different destinations, with higher travel speeds during midmorning or towards evening and the lower travel speeds being late morning or early afternoon.

Similar analyses were performed on specific origin/destination pairs. For travel times, the results indicated that there were fluctuations regardless of the OD pair. However, the level of fluctuation was OD pair dependent. These fluctuations might have been fairly small, between 5–15 minutes (as was seen from the University of Utah to the Intermountain Medical Center) or fairly large, such as 30–40 minutes as seen from the Salt Lake International Airport to Hill Air Force Base. Most of the smaller fluctuations occurred during the early morning hours of 7am or 8am as well as during midafternoon. The higher fluctuations tended to be slightly later in the morning, as well as during the midday around noon.

Once the service levels were examined for differences, social inequality was investigated to certain destinations based on the demographics of the origins. By examining the transit travel times and the transit travel speeds, it was clear that while higher levels of inequality were witnessed when looking at the travel times, the level of inequality diminished greatly when examining the transit travel speeds. However, while the inequality diminished, the results still indicate that the transit network provides better service for some sociodemographic groups than others. Even though there were differences, the differences noticed by this particular analysis are fairly negligible. For example, those that have higher income tended to also have higher travel times while those with lower income had lower travel times. While there is obviously an imbalance because both of the income groups do not have equal travel times, lower income groups rely more heavily on the public transit as their main mode of transportation. This makes transit a necessity, while those who have higher income can afford private automobiles and have other transportation options. Therefore, while there is some obvious inequality, depending on the situation, this inequality could be seen favorably by transit authorities and government agencies. Simply stated, transit dependent populations are actually being served by good transit service.

Lastly, this research examined travel surveys in order to determine if service is being provided equally for all of the different demographic groups based on each group's travel demand. This was performed by combining the cube with the trip information. Using the cube, the transit travel time to get from the origin to the destination at the time the trip was performed was determined. The resulting travel time was then compared to the average travel time for the entire day for that particular OD pair to determine if that person traveled when service was better or worse than average. Similar to the results for the previous section, differences were noticed between the different demographic groups. However, this time, the differences require more attention. The most important examples being that those with higher household incomes generally travel when the transit network is providing the best service compared to those that have lower household incomes. Also, those that are more educated, and therefore might have a better paying job, travel when the transit service is good, compared to those that are less educated who travel at times when the transit network is poorer. Lastly, those with the most amount of cars traveled at times when the transit service was providing better service than those that have one or even no vehicle. Therefore, it appears the transit network provides better service for those that might not actually need the service, but poorer service for those that might heavily rely on the service.

This research demonstrated how a public transit travel time cube can effectively be used to investigate accessibility. The cube consists of public transit travel times from all block groups to all block groups with start times at every minute of the day. One cube was constructed for a representative weekday and additional cubes for Saturday and Sunday. By aggregating over different sets of origins and destinations, the research demonstrates several methods for assessing accessibility. First, and most generally, transit travel times were summarized over all origins and destinations in order to investigate temporal fluctuations in overall network quality. Following this, origin/destination pairs were classified by Euclidean distance and direction of travel in order to investigate spatial patterns in accessibility. Next came a series of analyses investigating connectivity between specific nodes of activity in the region. And lastly, the cube was fused with travel demand profiles from two recent travel surveys. Throughout the work is an emphasis on assessing social inequality in transit service provision.

Based on these findings, several recommendations can be made. One of the major differences between the weekday/Saturday to Sunday is the lack of FrontRunner service. Adding FrontRunner service, even in a limited capacity, on Sunday would substantially help bring down the travel times for Sunday travel, providing a regional transportation benefit. Another recommendation would be to either invest in additional TRAX lines (similar to the new Sugar House “S” line) to link the east to west destinations with more frequent service. This could also be accomplished by providing east-to-west oriented buses more frequently, perhaps as frequent as every 10 minutes. I believe that with improvements in these two main areas, service levels would improve as well as sociodemographic equality. Lastly, using tools such as those introduced in this research to examine how well the current network is providing socially equitable service, planners can make modifications accordingly in attempts to correct any undesirable inequality.

1. INTRODUCTION

1.1 Background

In Transportation Geography, the study of *accessibility* is of vast importance. Accessibility is a hard term to define, but in its earliest form has been described as "the potential for opportunities of interaction" (Hansen, 1959). In contemporary literature, accessibility has been loosely defined as a measure of "the ease with which people can reach their opportunities or services," including health services, affordable food locations, and employment opportunities (Lei, 2010). According to O'Sullivan et al. (2000), "the goal of any transport system is not mobility *per se*, but access to facilities" (p. 86). An extensive number of studies have been conducted that illustrate the growing interest in the accessibility to different types of destinations and locations, such as trauma centers, general practitioner services, affordable food, and especially employment (Branas et al., 2005; Coveney & Dwyer, 2009; Lei, 2010; Lovett et al., 2002; Tomer, 2012).

One of the most important aspects in determining an individual's level of access to and from a destination is the mode of transportation chosen, such as private automobile, foot, bike, public transportation, or any other mode. Similarly, why an individual chooses a particular mode of transportation may involve a variety of factors, including cost, convenience, travel time, reliability, ease-of-use, and physical access to the particular type of transportation (Beirao & Cabral, 2007).

Social factors also affect an individual's choice of transportation. For example, affluent individuals who can afford private automobiles are more likely to use them for work commutes, trips to the store, and other activities requiring travel. By contrast, those who cannot afford their own private transportation are more likely to rely on the other modes, such as walking, bicycling, or public transportation. Social and economic factors also help to explain why individuals of less affluence regularly choose residential locations based on the accessibility they offer to work, health care, and transportation (Foth et al., 2013).

Finally, research has shown that different social groups within a population travel at different times of the day. For instance, most individuals in the professional and managerial labor force work during the typical daytime hours of 9am to 5pm. In contrast, individuals in the manufacturing, service, or retail industries are often expected to work in the evening or overnight hours (Jena et al., 2012). Because of the disparity in earning potential, these individuals are also much more likely than their counterparts to carry multiple positions and work a variety of shift hours.

Public transportation accessibility has been studied extensively in transportation geography. Various methods have been used to understand the accessibility provided by public transportation networks. The earliest studies focused on accessibility to the network itself, referred to as *system accessibility*, normally using Euclidean distance or network distance buffers around stop locations (Murray et al., 1998; O'Neill et al., 1992; Zhengdong et al., 2008). Recently, the focus has shifted to the accessibility to specific destinations and locations. These studies use coverage areas, wait-times, travel-times, and shortest-paths to assess how individuals might use public transit to access destinations such as shopping centers, stadiums, hospitals, employment opportunities, and universities (Lei & Church, 2010; Mamun & Lownes, 2011a; O'Sullivan et al., 2000; Rood, 1998).

Other studies have emphasized the accessibility to destinations provided by a public transportation network by sampling select parts of a region. For example, according to a report published by the Metropolitan Policy Program at the Brookings Institution, Salt Lake City and Provo, Utah, are currently listed in the top 10 of the greatest levels of access to work places by a public transit network out of the nation's 100 largest metropolitan areas. This study measured how easily workers could use public transit to travel to work, but ignored the other types of destinations and the experience of nonworkers. Also, while the methodology behind the study will be discussed later, it is important to note that the study of accessibility was conducted during a representative Monday morning commute, between the hours of 6am and 9am, when the authors believed that 65% of the workforce would be traveling to work (Tomer, 2012). Even if this estimate was accurate, this would leave 35% of the workforce, let alone the remaining transit users such as unemployed individuals or stay-at-home parents, unaccounted for. An independent study using the 2012 Utah Travel Survey found a similar finding, with 60% of all transit trips being taken during peak travel times. This again shows that 40% of transit trips are often unaccounted for using the previous types of methods.

The methods in the previous literature measuring the accessibility provided by transportation networks reveal a similar trend: all employ a single fixed time analysis for studying accessibility (Henk and Hubbard, 1996; Kittelson & Associates, 2003; Murray et al., 1998; O'Sullivan et al., 2000; Rood, 1998; Tomer, 2011; Wu and Hine, 2003).

Because most of these studies have a restricted focus on fixed-times, especially rush hour, the studies undoubtedly are limited to only highlight accessibility to employment locations for workers who rely on public transportation. While the labor force is an important part of the population, the exclusive attention to this group may neglect individuals who rely on public transportation for other purposes, such as to get to health services and affordable food locations.

Different social groups in the population also rely on public transportation in different ways. As stated, economic factors may increase the rate of private automobile use in middle and upper class communities while diminishing reliance on public transportation. On the other hand, less affluent individuals are more likely to rely on public transportation, unless they live close enough to destinations to walk or bike. As previous studies have revealed, less affluent populations tend to congregate in residential areas near their place of employment to help lower travel time and cost (Foth et al., 2013). However, where this is not possible, heavy reliance on public transportation networks is still common.

Studies have also shown that different racial groups tend to rely on transportation in contrasting ways. In the United States, while Caucasians/Whites tend to rely on cars to commute to and from work, African Americans and Hispanics rely heavily on the public transportation network. African Americans are also more likely to refuse jobs because the public transit commute time is excessive (Patacchini & Zenou, 2005). As Kain (1968) pointed out in the famous “spatial mismatch hypothesis,” these minority groups are often geographically restricted to the inner cities and away from expanding employment locations, which often leads to continued hardships in searching for and holding onto well-paid employment opportunities. Since then, however, some have argued that the problem is not as much geographic (such as physical distance or barriers) but travel mode choice and the resulting travel time (since cars often get to destinations faster than public transportation; Grengs, 2010). However, the public transportation network of some cities continues to enhance this dilemma, with good accessibility for the downtown areas where lower paid jobs may be located, but a lack of accessibility, including nonexistent service or excessive travel times, to the periphery of the city where better jobs are often being offered (Patacchini & Zenou, 2005).

In addition, the need for public transportation networks that operate during off-peak periods may be especially important for individuals who work evening or night shifts or must run errands during off-peak hours. Utah Transit Authority's (UTA) transit network schedule is easily available online (www.rideuta.com) and also has been implemented into Google Maps. Looking at the transit schedule clearly illustrates that the UTA's public transit network as a whole does not run continuously (usually only in full operation from 5am until 10pm), and also some sections of the network do not run continuously during the day, with trips from origins to a destination delivering typical rush hour service with no other trips being made for that particular route throughout the rest of the day. As a result, potential transit users who would find the route useful during the non-rush hour times are forced to find an alternative option.

For these reasons, it is important to gauge whether or not public transportation services provide adequate equal access from all origins to all destinations for the whole population across an entire day and not just at one particular fixed time segment, such as 6am to 9am. This research project will formulate an accurate method for calculating and determining if and how public transportation accessibility varies during a normal weekday, Saturday, and Sunday along the Wasatch Front (Figure 1), and if and how this might result in social inequality in the population. This resulting method could potentially be modified and used by other researchers and/or other areas of interest to help better accurately determine the spatial and temporal aspects of social inequality.

1.2 Problem

In order to understand how accessibility to destinations using public transit fluctuates during a typical weekday, a dynamic temporal analysis of the public transit network must be performed. The research includes Saturday and Sunday service hours when the schedule experiences a multitude of changes compared to the weekday schedule. In addition, the research seeks to determine how the fluctuations in the network compare with the “demand profiles” (times when traveling occurs) exhibited by the different social groups in the population. For example, does the network provide sufficient access to affluent areas during times of the day they are less likely to use it? And does it neglect less affluent communities during the times of day when they rely on it the most? The results of comparing the fluctuations with the demand profiles will help to highlight areas where spatial and temporal aspects of social inequality exist.

This research will attempt to answer several major research questions:

1. *How does accessibility via public transit vary over time?*
2. *How can the temporal variations in accessibility be measured and visualized?*
3. *How can transit network supply and travel demand be combined to highlight social inequality?*

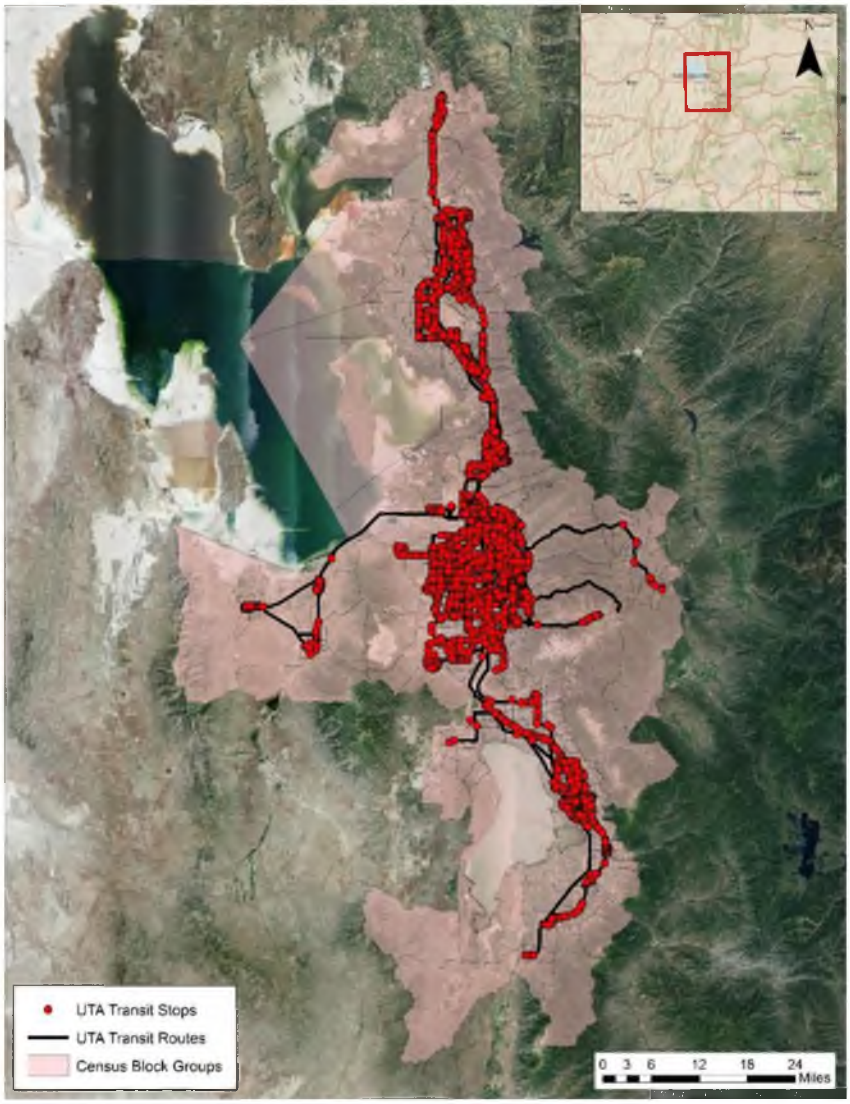


Figure 1: Wasatch Front study area in Utah.

1.3 Goals and Objectives

This research will attempt to fill in the gaps from previous studies that focused predominantly on accessibility to employment destinations using public transit during fixed time frames. This will be completed by instead performing a temporal analysis of public transit accessibility on a weekday, Saturday, and Sunday to determine the ease of using the public transportation network to reach all types of destinations, including employment centers but also medical care, shopping centers, airports, and educational facilities. Additionally, the research will attempt to broaden the scope of public transit accessibility by comparing the temporal fluctuations in accessibility with the travel demand of different social groups based on social factors such as income, age, and job classification. This will be completed by performing four objectives:

Objective 1: Develop a method to compute, describe, and visualize accessibility on a temporally dynamic public transit network.

Objective 2: Use the results of the method from Objective 1 to perform an analysis of the variability in travel times (minimum, maximum, average, etc.) for the entire study area, as well as examine directional trends (vertical/horizontal) in travel times and travel speeds to determine how the travel times and travel speeds are associated with the distance between origins and destinations.

Objective 3: Use the results of the method from Objective 1 to examine specific origin to destination pairs while also examining the social groups of the origins / destinations to highlight where (and when) social inequality exists.

Objective 4: Use two separate travel surveys conducted in Utah to examine when different social groups take trips and to conclude if these trips are being taken at times when the transit travel time is above, below, or near the daily average.

2. LITERATURE REVIEW

A large amount of research has been conducted in an attempt to quantify accessibility. The existing research will be introduced so that previous objectives and methods can be better understood. First, there will be a review of transportation and public transportation accessibility. Second, the social aspects of the accessibility provided by transportation networks will be explored. Last, I present a comprehensive review of how others have measured public transit accessibility, along with an introduction to the limitations of the previous methods and how this project will attempt to correct them.

2.1 Accessibility

Whether considering economic, environmental or social impacts, transportation systems are pivotal to regional development. It is the transportation system that allows for economic and social opportunities, with an ineffective system being a hindrance to these opportunities (Murray et al., 1998). A system can be ineffective for several different reasons, such as high fares, lack of comfort, and poor conditions, but most often it is considered ineffective because it is classified as providing poor accessibility from origins to destinations.

Accessibility can be considered as the ease in which a system can transport an individual from an origin to a destination (Murray et al., 1998). This concept differs greatly from the term *access*, which is the ability to use a system based on its proximity or cost. While being able to physically access a system is important, if the travel-time is extensive, the motivation of using the system diminishes. As Páez et al. (2012) argue, "it is reasonable to anticipate that as long as the friction of distance continues to exist, accessibility will remain a relevant component of transportation studies" (p.141). As cities continue to expand outwards as a result of urban sprawl, accessibility will continue to be of vital importance to researchers and transportation planners. While many different modes of transportation exist, one of the most widely researched is public transit (or public transportation). This mode of travel typically includes buses, light rails, subways, and commuter trains and is the major topic of this current research.

2.2 Social Aspects of Transportation Accessibility

While the study of social issues in transportation is not new, this research focuses only on the related research performed relatively recently (post-1990). During this time, social justice and social inclusion have taken prominent positions. In short, social inclusion is a "response to structural barriers that deny individuals and groups the ability to participate fully in the benefits of society, with particular attention to access to resources, such as goods, services, power, and control" (Scharlach & Lehning, 2013, p. 113). Similarly, social justice is the "fairness in the physical distribution of goods, accessibility for people, affordability of all types of services and distribution of other gains" (Beyazit, 2011, p. 117). Farrington and Farrington (2005) argue that in order for social justice to be met, social inclusion is required. However, it is important to note that they also argue that having social inclusion in and of itself does not result in social justice being obtained. Therefore, other factors need to be explored in order to better understand social justice in transportation.

In addition, according to Beyazit (2011), many of the current transportation policies disregard the socioeconomic diversity of individuals. Therefore, the need exists to implement transportation policies that allow for social equality. While differences between social groups are of interest, van Acker (2010) argues that behavioral differences in travel exist within social groups and should be studied as well.

Al Mamun and Lownes (2011a) discuss that public transportation is considered a crucial component in the growth of cities. It allows individuals to have greater opportunity, choice, and access to a variety of economic and social activities. As a result, the accessibility for individuals to service areas such as employment is a growing issue, especially for the working poor.

Rogalsky (2010) states that those who rely on public transportation to travel to work or other service areas tend to travel shorter distances due to the longer and somewhat excessive commute times, while those with private automobiles have the luxury of traveling longer distances while still maintaining reasonable travel times. Therefore, the accessibility provided by the public transportation network for those individuals without private transportation is extremely important. As mentioned, while the accessibility to employment locations is an enormously vital purpose of a public transportation network, so too is the accessibility to other locations, such as shopping centers, health care facilities, and universities.

Recently, many studies have focused on social inequality, especially in regards to transportation. Jaramillo et al. (2012) focused on the spatial disparity that exists in the public transit network of Santiago de Cali, Columbia: a network on which 70% of the population relies for transportation. They found that the areas with the worst socioeconomic conditions were the farthest from the central city and provided the poorest accessibility by the transit network.

Beyazut et al. (2011) studied how social justice is handled in transport systems and concluded that a more combined approach needs to be implemented in which those interested in social justice and those interested in transport policies work more closely together to create a network that provides equal accessibility to all demographic groups.

Morency et al. (2011) investigated population groups at risk of social exclusion (low income, elderly, single parent) to determine the different factors that influence how far people travel to reach their destinations. It was found that the target groups tended to travel shorter distances than the other population groups. This, in combination with a lower concentration of opportunities where these groups lived, resulted in poor accessibility for these groups.

Páez et al. (2010) attempted a similar study focusing on food deserts in Montreal that used multivariate, spatially expanded models to generate estimates of distance traveled for geographic locations and individual types. It was determined that overall, lower income groups tended to have fairly good accessibility to food locations when located near the center of the city. However, accessibility to food locations for the lower income groups decreased as the distance from the city increased.

Lastly, Casas (2007) used a travel survey to examine if disabled and nondisabled groups showed different levels of access and if so attempted to determine if disability was the main factor in their exclusion. The research concluded that disabled groups are more likely to have poorer mobility and accessibility. In addition, the mentally disabled had the biggest differences in mobility and accessibility out of all the disabled groups.

All of these studies focused on social exclusion in transportation, but most attempted to highlight if social exclusion existed and the factors that might contribute to it. From a planning perspective, while knowing if there is an existence of social exclusion and social inequality is important, it is vital to understand exactly where and when this exclusion occurs so that policies and changes can take place to make transportation and access to destinations more equal for all of the social groups in a population.

2.3 Methods of Measuring Public Transit Accessibility

Reviewing the previous literature of methods for measuring public transit accessibility indicates a stark difference between the types of analyses used. Most of the analyses were quantitative and could be split into two separate temporal categories: static and dynamic.

2.3.1 Quantitative Measurements

Most accessibility studies introduce new quantitative methods or add on to previous ones. The importance of quantitative methods is unquestioned, especially when dealing with public officials or policy makers who may be unfamiliar with transportation issues. In addition, two specific groups of temporal measurements have been discussed in the literature: static (accessibility analysis at a fixed time segment) and dynamic (accessibility analysis over different time frames).

2.3.1.1 Static Approaches

Recently, many new methods and techniques that focus on static approaches have been developed, both as stand-alone procedures and extensions to existing software programs, such as Esri's ArcGIS for Desktop suite. In order for the details of the various methods and techniques to be organized in a useful way to compare similarities and differences, a table was used (see Table 1).

The earliest methods and techniques examine how accessible the public transit network is across geographic space. Clearly, these types of methods are fairly simplistic and do not account for other factors that are of great importance to accessibility, such as the service coverage area provided by the network and the travel times from each origin to destination. However, even though the methods that included service coverage area are more useful for measuring accessibility than determining physical access to a public transit station, determining the spatial coverage and frequency of trips from a stop still lacks a temporal component. While a wide coverage area is crucial for a public transit network to be effective, if the travel time from an origin to destination is excessive, the accessibility is still considered poor. Understanding the travel time from an origin to a destination is essential in determining accessibility. However, most of these studies that incorporate travel time do so from transit stop to transit stop, without taking into account travel time from the origin to the transit stop, and from the transit stop to the destination. In addition, these travel times are normally calculated at a fixed time segment, which is not indicative of a temporally dynamic transit network.

By combining several metrics together, such as examining service coverage and travel times, studies have continually been improving the way that accessibility has been measured. However, even with these combination techniques, important factors have been excluded, such as how the service area coverage and travel times vary throughout a typical day. While rush hour service is important, using this as a measurement of the network as a whole ignores the temporally dynamic nature of a transit network and

Table 1: Comparison of static approaches for measuring public transit accessibility.

Author/Source	Method Type	Brief Technique Description	Results
Murray et al. (1998)	Buffer	Euclidean buffers placed around transit stops to illustrate access's dependency on distance.	Areas in buffers considered to be part of transit networks' coverage area.
O'Neill et al. (1992)	Buffer	Distance buffers placed around whole transit network.	Individuals residing in buffer zones have access to the transit network.
Zhengdong et al. (2008)	Buffer	Two main techniques. Buffers similar to previous two methods and distance-decay approach.	Distance-decay approach states that as the distance from the transit stop increases, the likelihood of the individual to use the transit stop (or network) decreases.
Rood (1998)	Local Index of Transit Availability (LITA)	Three scores: capacity (the seat-miles per capita), frequency (the total number of daily transit vehicles), and service coverage (the number of stops/stations per square mile) are created for a small area. All of the scores are added together to create overall score.	The scores from the different areas within a city or community can be examined to determine the areas where transit provides good accessibility (and therefore a good place for development) or else poor accessibility (and if destinations of interest are already located there, how to modify the network).
Drew and Rowe (2010)	Modified gravity-model	The gravity-model deals with distance-decay, or the assumption that as distance increases, the rider's willingness to travel decreases without a significant pull factor.	The method used a series of scenarios, such as the locations of stops and routes, to determine the impacts that each scenario had on social equality to planned services and facilities.
Kittelson and Associates, Inc. (2003)	Transit Capacity and Quality of Service (TCQS)	Integrated four criteria into advanced measure. 1) Transit stop located near area of interest, 2) Safe pedestrian conditions, 3) High frequency of service, 4) Transit available when there is demand.	
Al Mamun and Lownes (2011)	TCQS, LITA, and time-of-day tool.	LITA measure examines transit service intensity whole TCQS examined the area covered by the transit network.Time-of-day tool creates a needs index that explores when individuals travel.	Objective of the method was to study the transit needs of a population, as well as public transit accessibility to determine areas where spatial gaps exist in providing accessibility.

Table 1 (continued)

Author/Source	Method Type	Brief Technique Description	Results
Henk and Hubbard (1996)	Index of Transit Service Availability (ITSA)	Similar to LITA that measure system capacity, service coverage, and frequency.	Difference from LITA is that ITSA can also be used to compare transit networks in different urban areas with similar demographics.
O'Sullivan et al. (2000)	Space-Time	GIS application that generated isoschones (contour lines of equal travel-time from a specific location) for the public transit network based on space-time locations.	Authors felt that visually showing the travel times using isochrones would allow for easier analysis and better visualization.
Lei and Church (2010)	Transit Accessibility Planning Analyst (TAPA).	Utilizes the Dijkstra algorithm to determine the best (shortest) path from an origin to all possible destinations accessible from that origin point. The *TAPA* method, similar to the O'Sullivan method, also implements a way to determine travel-time from a specific location.	
Lei et al. (2012)	Shortest-Path	Used a schedule-based shortest-path algorithm to determine transit accessibility of population centers.	In order to conclude what destinations could be reached within a certain time-frame, the researchers used the farthest that an individual would typically travel using a public transit network.
Cheng and Agrawak (2010)	Time-Based Transit Service Area Tool (TTSAT)	Application to help policy makers and officials measure public transit accessibility for their area of interest. The application allows for users to add travel time into the service coverage measurement and select different measures based on desired outcome.	
Liu and Zhu (2004)	Accessibility Analyst GIS tool	GIS tool that determines public transit accessibility based on several component measures including opportunity-based measures (or the number of destinations that are within a specific distance of the origin), gravity-type measures (which measures the potential of a destination based on its size and the distance between destination and origin), utility-based measures (based on consumer supply), and space-time measures (the range and frequency of an individual's activities).	
Al Mamun et al. (2013)	Transit Opportunity Index (TOI)	Newer method that combined a measure of accessibility with the level of transit connectivity that is determined by space, time, and trip coverage.	One advantage of this new technique is that it could be used to determine transfer zones for transit trips even when no direct connection exists.

Table 1 (continued)

Author/Source	Method Type	Brief Technique Description	Results
Transport of London (2010a, 2010b)	Public Transport Accessibility Levels (PTALs)	Measure that takes into account ingress walking times, trip times, and egress walking times. Averages travel times from origins to destination based on "random" trip times.	The technique for measuring *(PTALs)* argued to be so straightforward that it is deemed too simplistic. For example, accessibility for different travel modes (e.g., bus or rail) are measured at fixed time segments, but these methods do not allow for changes to traffic patterns and congestion that might affect accessibility throughout the day (e.g., during peak rush hours).
Wu and Hine (2003)	PTALs	Implemented the *PTALs* measurement system using GIS and ACCMAP (a software package that specializes in measuring "accessibility to and from any point based on travel costs through highway and public transport networks"; [p. 308]) to measure accessibility achieved by the bus service in Northern Ireland.	However, they do note that the method, while useful in a well-connected city, does not perform well in rural areas and should therefore only be used in population-dense locations.
Tomer (2011)	Combined Metrics	Like most studies, several metrics were used in determining overall accessibility in this research. These measures include ones that target service coverage, service frequency, and job access. In addition, the authors also attempted to measure accessibility for the different working classes, as well as the accessibility to different types of jobs (low-, middle-, and high-skilled).	The study, performed for an average Monday morning commute, attempts to determine how well workers can access jobs using public transit. Obviously the fixed-time analysis is a pitfall that is the purpose for this research.

results in overestimation of accessibility during the off peak times.

2.3.1.2 Dynamic Approaches

Only three studies incorporated a dynamic approach over the fixed approach. While the fixed approach would investigate the accessibility without a time component, or during a specific time-frame, such as rush hour, the dynamic approach focuses on how accessibility changes throughout the day. Ryus et al. (2000) developed a *Transit Level-of-Service Indicator (TLOS)* for Florida, which the authors argue could be viewed as a real-life example of the *TCQSM* method mentioned earlier. The transit accessibility measure of this method is considered more robust because it requires extensive input data, such as detailed schedule information. For this measure, the accessibility indicator is the percentage of person-minutes being served by the transit network. For a particular area, this is calculated by first examining the percentage of people who can physically access the transit network without barriers (for example, only 50% of the population of the area can access the transit stops). In addition, the length of time that service is provided (such as a transit mode waiting at a stop for 5 minutes, six times per hour, equaling transit availability of 30 minutes or 50% of an hour) is determined. Therefore, the TLOS value for that particular area for that hour would be 25% (because 50% of the population can access the transit service, which in turn is only available 50% of the time). If the service ran for an entire day, the final TLOS for that area for the day would be 25%, but if the service only ran from 6am to 6pm, or 50% of the day, the actual TLOS value for that area for the day would be 12.5% (Ryus et al., 2000).

Polzin et al. (2002) employ a dynamic temporal analysis to measure transit accessibility and availability over time. By using different available data, such as local surveys or the Nationwide Personal Transportation Survey (NPTS) to determine when travel demand is high, specific time frames, such as 3am–4am, 6am–7am, etc., could be examined. The authors mention that accessibility would be more beneficial during times when demand is high (e.g., rush hour) and less important when demand is low. The study determines the service availability during each time frame (hour intervals in this case), and the time frame is weighted by the travel demand during that period, with times of higher demand being weighted more heavily.

Lastly, Andrew Owen and David Levinson of the Accessibility Observatory at the University of Minnesota (2012) released a technical report that also examined how transit travel times were different depending on the time of day. Similar to this current research, the study by Owen and Levinson understood the importance of GTFS data and how it could be used for schedule-based analyses. However, similar to other studies mentioned, this study too only compared fixed-time frames by examining the difference in transit travel times between AM peak (7:00–9:00am) and PM peak (4:00–6:00pm).

Unfortunately, these studies only measure if public transit is considered available, which is determined by frequency and wait time, but does not incorporate walk time to the transit stop, travel time, and walk time to the destination. These are crucial because even if the wait time is minimal, the total trip time to a destination could still be very high and therefore considered not realistically accessible. In addition, the study by Owen and Levinson compared how transit travel times are different between the AM and PM peak travel times but disregarded travel times outside of these peak hours.

2.3.2 Model Sensitivity

An important consideration when performing public transit accessibility analysis is the sensitivity of the models to user inputs. Several authors have performed studies that target a few of these sensitivities. Horner and Murray (2004) first mentioned the differences that arise when creating distance buffers around public transit stops. Some studies created Euclidean buffers around stops, normally 400 meters, and any area within the 400 meter radius was considered to have access to the transit stop (Murray et al., 1998). However, as Gutiérrez and García-Palomares (2008) argue, that method is fairly simplistic and does not resemble reality. Barriers, such as highways or buildings, cannot be traversed. Therefore, Gutierrez and García-Palomares argue that using a Euclidean buffer overestimates the coverage area, and a distance buffer using a street network is much more realistic (Gutiérrez & García-Palomares, 2008).

In addition to buffer distances, the sensitivity of geographic units is also of immense importance. Different geographic units were used as origins and destinations (census tracts, blocks, etc.) in many of the studies. This approach results in a scale issue, often referred to as the *Modifiable Areal Unit Problem (MAUP)*. Larger geographic units would tend to show coarser results than smaller geographic units. Also, for each of these units, the choice had to be made whether to use points (or centroids) in the center of each geographic unit or else depict the geographic unit as areal units (or polygons; Horner & Murray, 2004).

Lastly, these models suffer from barriers to transference; in other words, it is unreasonable to assume that the results from one study can be compared to another. Karlaftis and Tsamboulas (2012) highlighted this problem by examining 15 European transit systems. The authors used a wide range of frequently used performance assessment models (including neural network based efficiency measures and Cobb-Douglas Production Function based efficiency measures, along with 12 others) to compare how these models differed in regards to efficiency and effectiveness. It was determined that using different methods for a similar area of interest can often result in large differences in the measurements of efficiency and effectiveness. Since this research focuses on creating yet another measure of accessibility, this is an important concept to remember.

2.4 Synthesis

Many methods have already been developed to measure public transit accessibility. However, some of these methods are fairly simplistic (such as determining station access), with most of the previous studies focusing on the static approach to determining accessibility. More importantly, a fixed snapshot of the accessibility achieved by a transit network (typically during the busiest time) does not take into account the needs of those riders who use services during off-peak hours. During these times, service may become less frequent or cease operating altogether.

Earlier transit network accessibility studies have also ignored the diversity of the people that rely on public transportation. In previous studies, the emphasis has been almost exclusively on workers' accessibility to employment locations. While labor-force traffic is important, so too is the overall accessibility of the transit network for every type of travel demand, such as shopping, social activities, etc. Researchers must determine if and how the overall accessibility might change during the day by integrating an approach that takes into account all origins and destinations at different times of the day/night.

3. METHODOLOGY

3.1 Description of Study Area and UTA Services

The Wasatch Front (Figure 1) is located in north-central Utah and incorporates the major cities of Salt Lake City, Provo, and Ogden. According to the Wasatch Front Regional Council (WFRC; www.wfrc.org), this area is considered to be one of the fastest growing regions in the United States, with a combined population of 2.1 million people in 2009 and a predicted increase of 65% by 2040. Dozens of universities and colleges reside in this region, including at least four major universities (Weber State, Utah Valley University, University of Utah, and Brigham Young University) attracting even more individuals to the area. As the population increases, so too does the number of private automobiles being utilized to travel to work, school, and social activities. Due to the geographic layout of the Wasatch Front, with mountains to the east and west of most of the region, the increase in driving has resulted in deteriorating air quality during periods known as inversions. These periods of bad air have been contributed to health issues, and initiatives to promote alternative modes of travel have been expanding. One of these highly visible modes being the public transit system provided by UTA.

The UTA boasts some impressive ridership numbers, with the Salt Lake Tribune in March 2014 reporting that during 2013 there was a 3% increase in overall ridership while the national average during that time was only about 2.1%. The UTA transit system includes three main modes of public transportation, including light rail (TRAX), commuter train (FrontRunner), and bus. During 2013, the ridership percentages for TRAX and FrontRunner rose 6.8% and 103.26%, respectively. However, bus ridership declined by 8.4%. There are also smaller scale services provided by the network such as van pool and paratransit that are more difficult to track and were not included in the study because of that.

One of the newer modes of public transportation is the FrontRunner service, which runs from Ogden in the northern part of the study area to Provo in the southern part (with Salt Lake City in the middle). Using a higher speed dedicated railway, this mode covers the most distance but services only 16 stops. FrontRunner services each stop every half-hour in the morning and evening, and every hour during the middle of the day. On Saturday, FrontRunner only services each stop every hour for the entire day, and Sunday has no service provided at all.

Another mode that is fairly new and continually expanding is the TRAX light rail service. Currently, TRAX has three main lines, the blue line that connects downtown to Sandy and other southeastern suburbs while spanning 19 miles and servicing 21 stops, the red line that connects the University of Utah, downtown, and southwestern suburbs and covers a slightly longer distance of 23.5 miles in length and provides service to 25 stops, and the green line that connects the airport, downtown, and western suburbs while servicing 18 stops along its 15-mile route. However, each of the lines have a frequency of 15 minutes on a weekday, and 20 minutes on both Saturday and Sunday. The main difference between Saturday and Sunday being that the service begins a little earlier on Saturday and runs much later into the evening.

The last and most complicated major mode is the bus service. The bus service consists of 122 different routes, with a little over 6,000 stops located across the valley. The bus routes are complicated by the fact that different routes have different characteristics, with some routes running every 15 minutes, some running 30 minutes, some running every 60 minutes, and some running only twice a day (express bus). Also, some of the routes are in full operation 7 days a week, while others are only in operation during the weekdays. As will be discussed later in this research, these different modes of public transportation affect the travel times and speeds from origins to destination and are important when considering the spatial components of transit accessibility. Figure 2 depicts the transit network's layout across the study area.

Figure 2: UTA's public transit network along the Wasatch Front.

<u>3.2 Data</u>

This research required a variety of data and methods and was completed by first collecting and prepping the required data, creating and running a tool that generated the *public transit travel time cube* (henceforth referred to as the cube), and analyzing the cube in an effective way. The cube was used to examine the overall temporal differences in the public transit network, the temporal differences from specific origins to destinations, and lastly, the times that different social groups take trips and how well the network provided service to meet this demand.

<u>3.2.1 Network Data</u>

- The GTFS data that were crucial for this research were obtained from the official GTFS Data Exchange website (http://www.gtfs-data-exchange.com/). These data, which are uploaded by UTA, are a series of 8 separate text files. These files include agency (transit agency that provided the data), calendar (service start and end dates), calendar dates (dates of actual service within service start and end date), routes (transit routes), shapes (used to geographically extract the routes), stop times (times that a vehicle arrives and departs each stop on a trip), stops (individual locations where vehicles pick up or drop off riders), and trips (sequence of two or more stops). The particular GTFS package used for this research consisted of service dates ranging from 08/19/2013 to 12/7/2013, 122 transit routes, 6,202 transit stops, and 7,472 transit trips.
- Utah road centerlines obtained from the Utah Automated Geographic Reference Center (AGRC) (http://gis.utah.gov/data/sgid-transportation/) for

modeling egress and ingress times.

3.2.2 Demographic Data

- Census Blocks geometry with 2010 total population data from Utah AGRC (http://gis.utah.gov/data/demographic/2010-census-data/).
- Census Block Group (CBG) geometry from Utah AGRC (http://gis.utah.gov/data/demographic/2010-census-data/).
  - CBGs were chosen since they are the highest resolution census data that population, race, income, and other characteristics could be gathered for.
- CBG demographic data that were obtained from the American Community Survey (ACS) 2008–2012, 5-year summary (http://www2.census.gov/acs2012_5yr/summaryfile/). The characteristics for this research include
  - *Age:* Under 18, 18–64, Over 65
  - *Race:* White, Other Race
  - *Hispanic:* Not-Hispanic, Hispanic
  - *Education:* High School or Less, Higher Education (Some College/Associate/Bachelor/Master degree)
  - *Income:* Less than 35k, 35k–75k, 75k–150k, Over 150k
  - *Occupation:* Management/Professional, Health/Service/Sales, Physical Labor
  - *Employment:* Employed/Armed Forces, Unemployed/Not in Labor Force

  - *Disability:* Disabled, Not Disabled

3.2.3 Travel Data

- CBG journey-to-work data that were obtained from the American Community Survey (ACS) 2008–2012, 5-year summary (http://www2.census.gov/acs2012_5yr/summaryfile/). The characteristics for this research include
  - *Mode of travel to work:* Automobile, Public Transit, Other Mode
- Utah Household Travel Survey conducted in 2012 by the Wasatch Front Regional Council, the Mountainland Association of Governments, the Cache Metropolitan Planning Organization, the Utah Department of Transportation, and UTA. This survey took place between March and July 2012. Households were invited by mail to participate in the survey on a preassigned date. The households could use an online web survey form or call a toll-free number to complete the survey. The survey contained four main sets of data: household data, individual data, trip data, and vehicle data. For this research, only the household, individual, and trip data were required. The full survey consisted of 9,155 households, 27,046 individuals, and 101,404 trips (though as will be discussed later, a subset of this survey was used for this research). These data are used to determine when different demographic/social groups travel in the study area. The useful information contained in this survey includes
  - Trip Origin/Destination Coordinates
  - Purpose of Trip
  - Time of Trip Departure

    - Demographic Information of Trip Taker
        - Age, Gender, Employment Status, Education Level, Hispanic Status, Race, Mobility, Household Income, Household Size

- UTA On-board Survey conducted in March 2011 by the third-party consulting firm RSG Inc. Three methods were used to distribute the survey. Paper postcards were sent out to the population with a prepaid reply mail option. Email postcards were sent using UTA's email address database of more than 40,000 frequent and infrequent customers. Lastly, UTA staff also distributed paper form surveys to each person boarding a sampled trip. Overall, the survey contains 3,939 surveys from bus passengers, 2,378 surveys from TRAX passengers, and 802 surveys from FrontRunner passengers, for a total of 7,119. However, a subset of this was used for this research. The survey contains individual trip information for transit users. These data are used to determine when different demographic/social groups travel by transit in the study area. The useful information contained in this survey includes
    - Trip Origin/Destination Coordinates
    - Purpose of Trip
    - Time of Trip Departure
    - Trip Fare Type
    - Egress/Ingress Mode
    - Demographic Information of Trip Taker
        - Age, Gender, Transit Frequency, Number of Vehicles, Driver's License, Income, Primary Transit Mode

3.3 Methods

This research also required a variety of methods. The cube was used to examine how the transit travel times varied across the entire study area over different days of the week. The days examined included a Wednesday, Saturday, and Sunday. Wednesday was arbitrarily chosen because the network operates similarly Monday–Friday and therefore in order to reduce the computational workload of this research, only one day of the week needed to be examined. Saturday and Sunday, however, both demonstrated different schedules and were examined separately. In addition, how the transit travel times and transit travel speeds vary over Euclidean, horizontal, and vertical distance was examined to determine if any directional trends were evident in the valley. Similarly, the cube was also used to examine specific origin to destination pairs while also examining the demographics of the origins / destinations to highlight where (and when) social inequality exists. Lastly, the Utah Household Travel Survey and the UTA Onboard Survey were examined to highlight when different social groups take trips, as well as the adequacy of the transit network at providing service to meet this demand.

3.3.1 Generating the Transit Travel Time Cube

One of the main objectives of this research was to develop a method for computing a temporally dynamic accessibility measure using the Wasatch Front public transit network, and generating a cube:

$$T = \{t_{ijm}\}$$

The cube is a 3D matrix with entries t_{ijm} being the travel time from origin i to destination j at minute m. As such, the cube contains the travel time for every origin/destination (OD) pair in the study area at every minute of the day. As previously mentioned, cubes were generated for Wednesday, Saturday, and Sunday.

3.3.1.1 Collecting and Preparing the Data

First, population weighted centroids were created for each CBG using the "Mean Center" tool in ArcGIS for Desktop 10.1. These were used as the origins and destinations in the cube. While the true population weighted centroid was used in most cases, some centroids were manually adjusted to better reflect realistic origin and destination locations. For the University of Utah, the centroid was relocated to the center of the campus. For the airport, the centroid was moved to the main terminals.

Lastly, only centroids within 3 miles of the UTA routes and stops were included in the study. This is because an individual typically will not walk more than a mile to a transit stop (and certainly not 3 miles). These centroids were removed rather than moved as it was our intent to limit the amount of subjective interference with the data. Of the Wasatch Front's 1,394 CBGs, 1,326 (Figure 3) met the aforementioned criteria and were included in the study.

The study area's road network was needed to model ingress and egress travel times. Missing roads were discovered during a visual analysis of the data, especially around new light rail and commuter rail stations. To ensure that transit stops were properly connected to the road network, a spatial query was used to find all stops farther than 25 meters from the nearest road, and modifications to the road network were made. Certain irregularities and errors were found to be present in the road network (such as the lines at an intersection not connecting properly), which would result in inaccurate routing. Topology rules were created to locate and correct such errors.

Finally, major highways (Interstate 15, Interstate 215, and Interstate 80) and

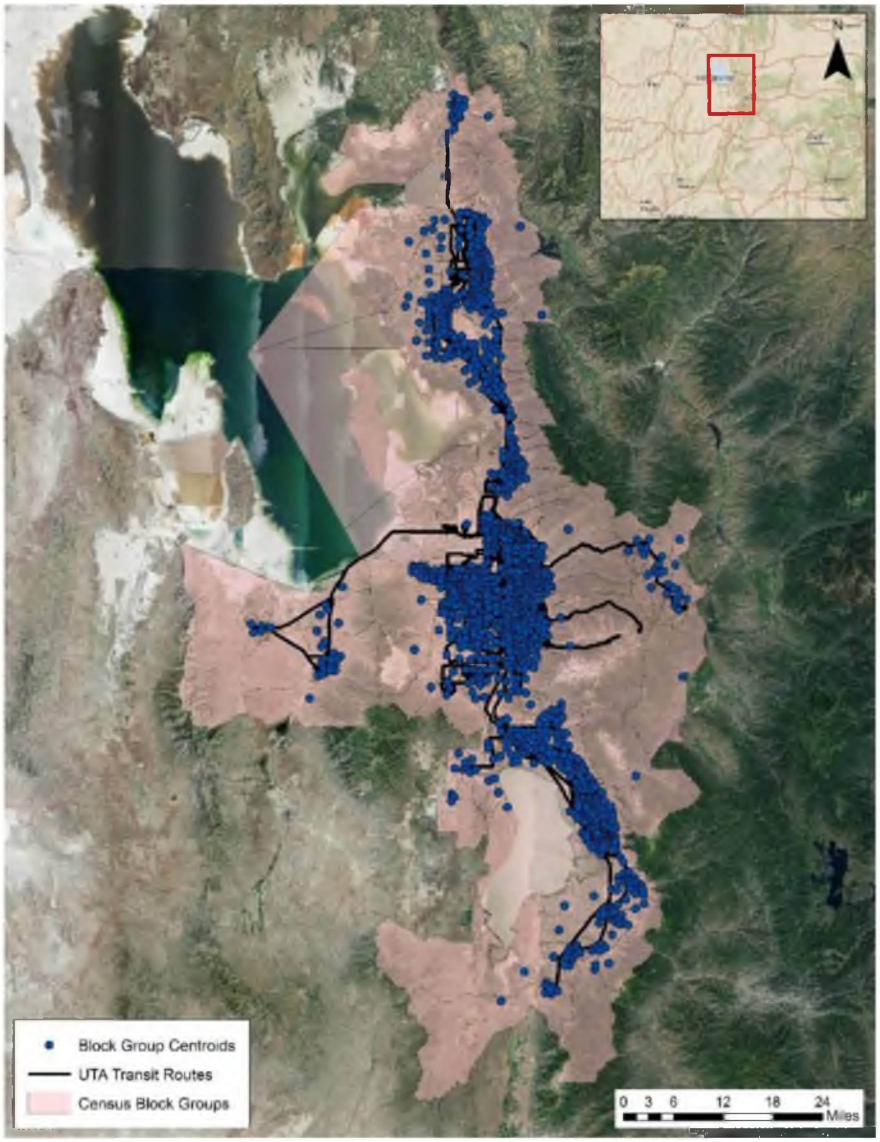


Figure 3: Wasatch Front's Census Block Group centroids.

ramps were each removed from the road network as these links cannot be used by pedestrians during ingress and egress.

The UTA transit network schedule is obtainable online (www.rideuta.com) and is available in the GTFS data format. These data can be integrated into typical Geographic Information System (GIS) software such as Esri's ArcGIS for Desktop suite. Because schedules are routinely modified and GTFS feeds continually updated, a decision needed to be made regarding which version of the data to use. During a typical year, UTA makes major modifications to the schedule in August and December. These modifications include adding routes, eliminating routes, modifying stop times or route times to connect better with other modes of transit, etc. GTFS data from August 16, 2013 were used in this research because they reflect the major modification that took place in August.

3.3.1.2 Creating and Running the Temporal Analysis Tool

The beta tool *AddGTFStoNetworkDataset (v 0.1)* created by Melinda Morang, a programmer at Esri, incorporates the GTFS data into a routable Network Object for the ArcGIS Network Analyst extension. Network Analyst can then be used to find the fastest transit trip (including walking and waiting times) between any set of origins and destinations using a specified departure time

Custom Python scripts were needed to compute the fastest travel-time from each origin (CBG population weighted centroid) to each destination (CBG population weighted centroid) for every minute of the day. This travel time consisted of the ingress and egress walking times, waiting times, transfer times, and in-vehicle travel times. Note that a walking-only route may be returned if it is indeed determined the fastest route.

Certain topological elements were constructed in the process of creating the network dataset (ND). These primarily consisted of line-connectors between CBG centroids and the pedestrian network and between the pedestrian network and transit stops. Code was written to automate these processes.

Figure 4 shows the connectivity groups that were used in the creation of the ND. Connectivity groups were used to model how people were allowed to transfer between different types of features on the network. Three separate connectivity groups needed to be created. One for streets, one for the stop-street connectors, and another for the transit

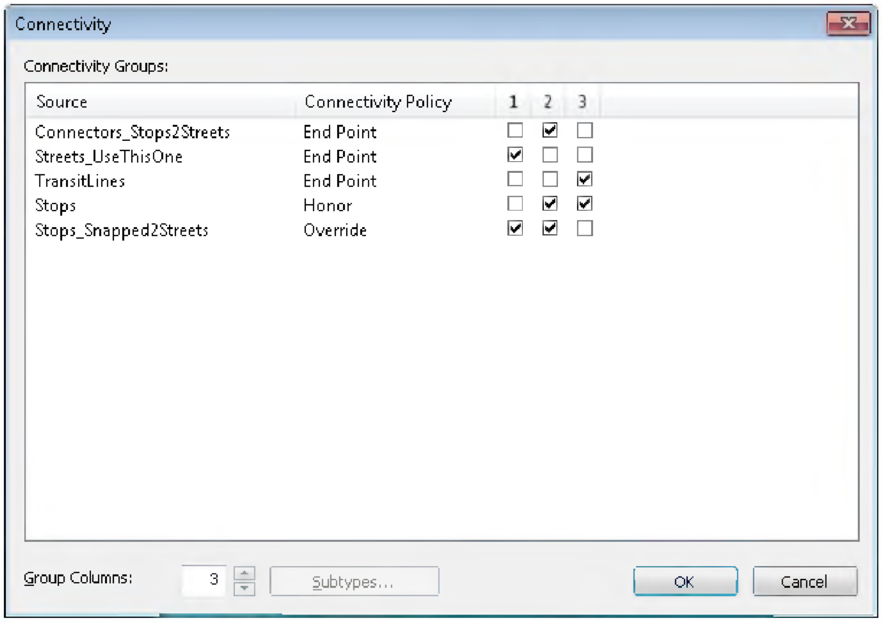


Figure 4: Network Dataset connectivity parameters.

lines. The connectivity policy *End Point* was used for some of the features because these features cannot connect to each other except at end points. *Honor* was used for stops because stops should only connect to transit lines and connectors at endpoints. Lastly, *Override* was used to allow the snapped stops to connect to the street feature vertices even if the street feature connectivity was set to *End Point*. In the end, this connectivity logic allowed for pedestrians to transfer to/from the transit network only at designated stops.

Next, evaluators for travel cost were defined for each type of feature traversal (Figure 5). For *streets*, Length/80.4672 was used to compute walking time because 80.4672 meters per minute is equivalent to 3 miles per hour, the average adult walk speed (Schimpl et al., 2011). For the *stop/street connectors*, a value of 0.25 approximates 15 seconds for boarding and exiting vehicles. Finally, for the *TransitLine*s, a custom evaluator Dynamic Link Library (DLL) packaged with the add-in was used to compute travel times. However, because the routes were only one-way, only the “from-to” option

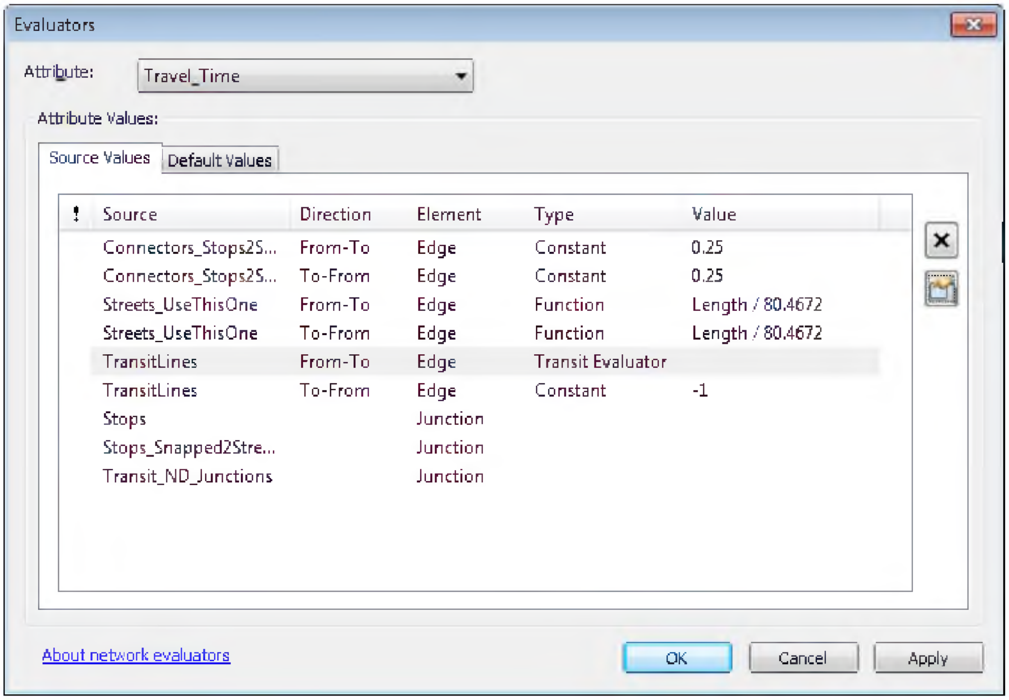


Figure 5: Network Dataset evaluator parameters.

used the DLL file. The "to-from" option was set to -1, indicating that transit routes could not be traversed in the reverse direction.

With the ND in hand, a tool was developed to compute travel times for all OD pairs at every minute of a weekday, Saturday, and Sunday. This automated the extremely time consuming manual process of computing cost matrices 3x1440 = 4,330 times. Even though the process could be automated, on a typical desktop computer each minute of the day took around 60 minutes to calculate. On our quad-core machine, which has the capacity to run three simultaneous ArcGIS processes, 3 cubes was estimated to require 60 days of computation time. In order to substantially speed up the processing time, the infrastructure at the University of Utah's Center for High Performance Computing (CHPC) was used. CHPC temporarily allowed this research project to use two dedicated servers for processing the public transit travel times. The computational capacities of those servers allowed for 24 simultaneous processes to run. In the end, the processing time was significantly reduced to about 7 continuous days.

An additional problem arose when attempting to save the public transit travel time results into a useful file format. Software packages, such as Microsoft Excel, were not designed to handle the amount of data that were created. Using the *H5PY Python* library, I experimented with the *HDF5* file format, which was designed specifically for storing and managing high volume and complex data. However, querying this data format for analysis proved challenging, and Comma-separated values (CSV) files were used in the end.

The resulting 3 CSV files (1 per day) each contained approximately 42 million records. Each record consisted of an array of attributes, including origin Block Group ID, destination Block Group ID, the transit travel time for each minute of the day, and the Euclidean distance from the origin centroid to the destination centroid. Figure 6 details a snapshot of one of the CSV files, and Table 2 summarizes the type of data contained in the files.

3.3.2 Aggregate Travel Time Analysis (Wasatch Front)

Once the travel times for every minute of a weekday, Saturday, and Sunday were calculated and stored in CSV files, analyses could be performed to examine how the transit travel times fluctuate across the day, as well as perform a preliminary analysis into the vertical and horizontal differences in transit accessibility. Examining the directional trends was important because those familiar with the transit network understand that the faster travel modes, such as FrontRunner and TRAX, have a predominantly north/south alignment. At the same time, socioeconomic affluence tends to be concentrated in a north/south corridor. It was therefore important to determine if the infrastructure allowed

OBJECTID	ORGBG	DESTBG	SAT_000	SAT_001
1	490039605001	490039605001	0	0
2	490039605001	490039605002	35.39	35.39
3	490039605001	490039605003	30.39	30.39
4	490039605001	490039605004	41.69	41.69
5	490039605001	490039606011	32.72	32.72
6	490039605001	490039606012	44.52	44.52
7	490039605001	490039606013	40.24	40.24
8	490039605001	490039606014	49.54	49.54
9	490039605001	490039606021	49.59	49.59
10	490039605001	490039606022	54.21	54.21

SAT_2358	SAT_2359	OD_Distanc	OD_OrgBGDestBG
0	0	0	OD_490039605001490039605001
35.39	35.39	2056.39220	OD_490039605001490039605002
30.39	30.39	1917.90313	OD_490039605001490039605003
41.69	41.69	2856.41141	OD_490039605001490039605004
32.72	32.72	1849.86517	OD_490039605001490039606011
44.52	44.52	2578.40656	OD_490039605001490039606012
40.24	40.24	2405.25665	OD_490039605001490039606013
49.54	49.54	3102.16594	OD_490039605001490039606014
49.59	49.59	2394.46851	OD_490039605001490039606021
54.21	54.21	3271.77013	OD_490039605001490039606022

Figure 6: Snapshot of *Public Transit Travel Time Cube* results.

Table 2: Description of the variables/attributes from Figure 6.

Attribute	*Description*
ORGBG	Unique ID for Origin CBG
DESTBG	Unique ID for Destination CBG
SAT_000 - SAT_2359	Public Transit Travel Time from Origin to Destination if leaving Origin at the specified minute
OD_Distance	Euclidean Distance in meters between the origin and destination.
OD_OrgBGDestBG	Unique ID for Origin/Destination Pair

for better access if moving throughout the study area vertically, but not as good if moving horizontally.

Preliminary analyses suggested that results were overly impacted by long travel times to and from the extremities of the study area. Therefore, extreme locations were removed from the cube. The resulting study area used for analysis is shown in Figure 7.

Using the cube, a custom *Python* tool was created that calculated the summary statistics for each origin/destination (OD) pair. These statistics included the minimum

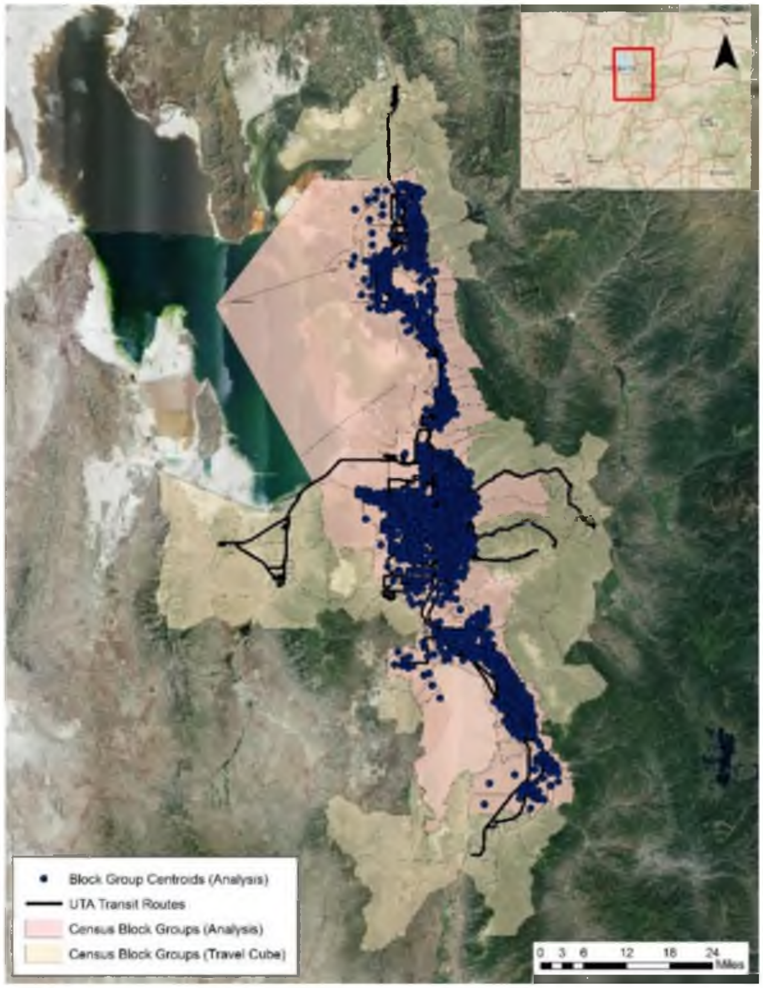


Figure 7: Revised Wasatch Front study area (red) for analysis purposes.

travel time, maximum travel time, range of travel times, average travel time, and the standard deviation of travel times. These statistics were calculated for all of the days (weekday, Saturday, and Sunday) and for three different analysis time segments. These segments were 5am–10pm, when the transit system was most in operation; all day; and hourly. In addition, statistics for travel speed were also generated. Speed was calculated as the travel time of the OD pair divided by the Euclidean distance between the pair. Euclidean distance was chosen to be robust to network configurations. The summary statistics were converted into graphs and charts for easier comparison of the network fluctuations that occur throughout the Wasatch Front. In addition, various maps of the study area were created that highlight the spatial aspect of how the travel times and speeds fluctuate between the different days of the week.

After the statistics were analyzed for the whole study, the relationship between travel times, distance, and orientation of the pairs was examined using *lowess* scatterplots. After trying a few different smoothing parameters, where the value is the proportion of points in the plot that influence the smooth at each value, 1/10 provided the best results in terms of highlighting significant local fluctuations while focusing attention on the general trend. These types of plots were created to examine how the average travel time, average travel time range, average travel time standard deviation, and average travel speed vary based on the Euclidean distance between the OD pairs.

Next, directional differences were analyzed. After some experimentation, it was determined that the most appropriate way to perform this analysis would be by examining OD pairs that had near-perfect north-south and east-west alignments within certain distances from each other. This allowed us to easily compare OD pairs with similar distance, but different orientation (vertical vs. horizontal). The vertical and horizontal distances were calculated using Universal Transverse Mercator (UTM) coordinates of the centroids.

Table 3 organizes OD pairs by directional distance and thresholds used to control for directionality. The distance range refers to the vertical and horizontal distances that were chosen for each grouping. The horizontal control is the horizontal distance that was used to limit what was considered a vertical OD pair, and the vertical control is the vertical distance that was used to limit what was considered a horizontal OD pair. For example, an OD pair was considered to be in the 2,001–4,000 vertical distance range if

Table 3: Vertical/Horizontal distance parameters.

Distance Range (m)	***Horizontal Control (m)***	***Vertical Observations***	***Vertical Control (m)***	***Horizontal Observations***
2,001–4,000	350	1,992	200	2,564
4,001–6,000	350	1,602	200	1,794
6,001–8,000	350	1,338	200	1,264
8,001–10,000	400	1,048	200	1,154
10,001–12,000	400	1,002	200	958
12,001–14,000	500	994	200	874
14,001–16,000	550	702	150	674
16,001–20,000	550	984	150	772

the vertical distance was between 2,001 and 4,000 meters AND the horizontal distance between the OD pair was 350 meters or less. Likewise, an OD pair was considered to be in the 2,001–4,000 horizontal distance range if the horizontal distance was between 2,001 and 4,000 meters and the vertical distance between the OD pair was 200 meters or less. The horizontal and vertical control numbers were chosen for each distance grouping in a way that the number of horizontal and vertical observations were similar. In addition, the groupings did not go above 20,000 meters because, while the study area was long vertically, it was only around 20,000 to 25,000 meters horizontally.

Lastly, similar to the Euclidean distance plots, *lowess* line plots were generated for each of the distance groupings with a smoothing parameter of ¼ where the value is the proportion of points in the plot, which influence the smooth at each value. These plots highlighted how the average travel time varied by the horizontal and vertical distances. In addition, average travel speed and average travel time range were also compared to the horizontal and vertical distances.

3.3.3 Specific Origins/Destinations Travel Time Analysis

After the analyses that examined how public transit travel times fluctuated across the entire study area, additional analyses were conducted in order to examine how public transit travel times fluctuate to specific destinations across the entire day. For this research, 10 different destinations were used ranging from the Salt Lake International Airport, to shopping centers, educational centers, and employment centers. Refer to Figure 8 for all of the destinations that were used, as well as their geographic location in the study area. In addition to how the transit time and speed fluctuated from all of the origins to these specific destinations, this analysis also examined the average time and speed that the different sociodemographic groups undertake in order to reach each of these destinations.

First, all of the sociodemographic data of interest needed to be obtained for each of the origin/destination CBGs. All of these data were downloaded from the Census Bureau's American Community Survey Summary 5-year summary file (2008–2012). Table 4 highlights the variables that were collected for each CBG.

A custom *Python* script was created to extract all of the origin/destination pairs and save them into a separate CSV file for each of the destinations to be studied. Once a separate CSV file was created for all ten destinations (10 destinations x 3 days = 30 total), they were converted into separate file geodatabase tables. Using the *summarize* tool in the ArcGIS suite on each geodatabase table, all of the OD pair records and their attributes were summarized into a single record that contained the desired statistics when examining the fluctuations in the network from all origins to the specific destinations.

These statistics included the avg. min. travel time ($\overline{MIN}$), avg. max. travel time

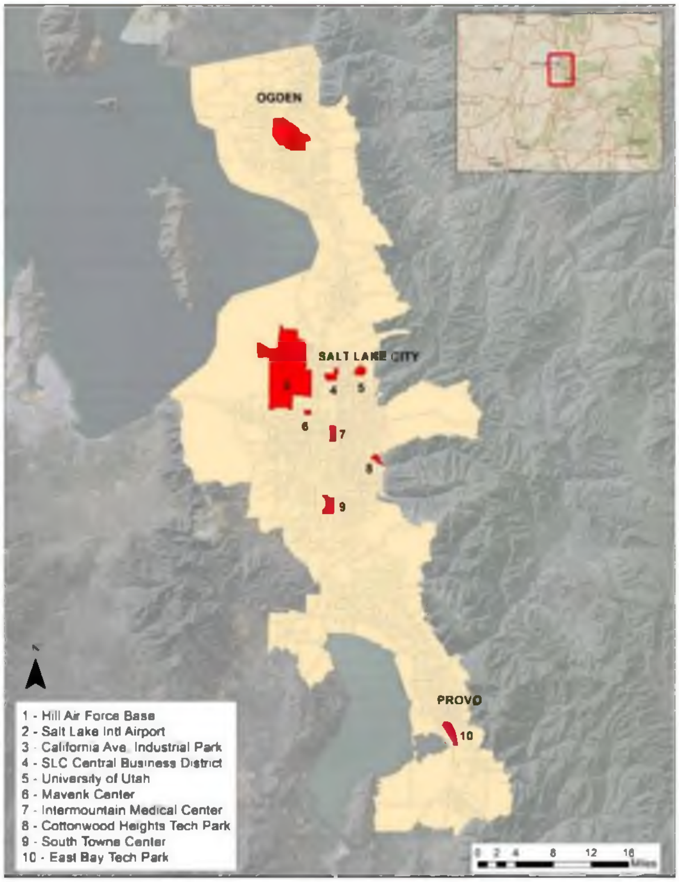


Figure 8: Locations of interest in the Wasatch Front study area.

($\overline{MAX}$), avg. travel time ($\bar{T}$), avg. travel speed ($\bar{S}$), avg. travel time range ($\bar{R}$), and avg. travel time standard deviation ($\overline{SD}$) for each of the days (as shown in Figure 9). A series of maps and graphs were used to explore temporal and spatial trends in the statistics.

After examining how the network fluctuated from all origins to each specific destination, a few of these locations of interest were chosen to examine how travel times varied by day and by hour from a specific origin to a specific destination. Again, a simple *Python* tool was created to extract only the OD pair of interest, including the actual travel time for each minute, the average travel time for each hour, the average travel range for each hour, and the average travel speed for each hour.

As with the previous analysis, the statistics included the average travel time

Table 4: ACS 5-year Summary File (2008–2012) variables.

Age	• Under 18 • 18–64 • Over 65
Race	• White • Other
Hispanic	• Non-Hispanic • Hispanic
Education	• High School or Less • Higher Education
Household Income	• Less than \$35,000 • \$35,000–\$75,000 • \$75,000–\$150,000 • Over \$150,000
Occupation	• Management/Professional • Health/Sales/Service • Physical Labor
Employment	• Employed/Armed Forces • Unemployed/Not in Labor Force
Disability	• Disabled • Not Disabled
Travel Mode	• Private Automobile • Public Transit • Other

$$\overline{MIN} = \frac{\sum_i^N \sum_j^N MIN_{ij}}{N \times N}$$

$$\overline{MAX} = \frac{\sum_i^N \sum_j^N MAX_{ij}}{N \times N}$$

$$\bar{T} = \frac{\sum_i^N \sum_j^N \bar{T}_{ij}}{N \times N}$$

$$\bar{S} = \frac{\sum_i^N \sum_j^N \bar{S}_{ij}}{N \times N}$$

$$\bar{R} = \frac{\sum_i^N \sum_j^N R_{ij}}{N \times N}$$

$$\overline{SD} = \frac{\sum_i^N \sum_j^N SD_{ij}}{N \times N}$$

Figure 9: Formulas of the various statistics generated for analysis.

minimum, average travel time maximum, average travel time, average travel speed, average travel time range, and average travel time standard deviation across each of the 3 days. In addition, the average travel time and speed for each of the hours of each day was also computed. In order to better visualize these results, graphs were also created that highlight how the average travel time fluctuated by hour from each specific origin to each specific destination.

The last analysis in this section attempted to create weighted average travel times for each sociodemographic group for the entire study area, as well as to the specific destinations previously examined. The weighted average travel time and speed for each sociodemographic group were calculated by multiplying the total number of individuals in the sociodemographic group by the travel statistic (time or speed) and then dividing by the total number of individuals in the sociodemographic group. For example, the weighted average travel time to destination j for population type k is

$$\bar{T}_j^k = \frac{\sum_i (P_{ki} \times \bar{T}_{ij})}{\sum_i P_{ki}}$$

where P_{ki} is the number of type k in CBG i, and $\bar{T}_{ij}$ is the mean travel time from i to j. Population weighted travel speeds were similarly created.

3.3.4 Adequacy of Supplying Sociodemographic Demand

The last section of this research focused on using the individual travel surveys conducted in Utah to examine when the different sociodemographic groups tend to travel. Using the time of the trips taken during these surveys, the travel time of the trip according to the cube was compared to the average travel time of that particular OD pair to determine if particular sociodemographic groups tended to travel at times when the public transit network provided good levels of accessibility or poor levels of accessibility.

For this analysis, two separate travel surveys were used. First, the Utah Household Travel Survey from 2012 was obtained. Because children tend to not make trip decisions, all of the participants under the age of 18 were removed. In order for the analysis to work, each trip needed to have geographic coordinates for the origin and destination. All of the trips that were missing at least one of these coordinates were removed from this study. Also, since the survey was for all of Utah, if the trips did not begin and end in the study area, they were also removed. Lastly, any trip that did not have a departure time associated with it was eliminated from the survey.

Using the date of the trip, the day of the week the trip occurred was determined. Reviewing the dates, all of the trips occurred on a Tuesday, Wednesday, or Thursday, so therefore on a weekday. In order to use the cube to examine the travel time of the trips, a spatial join was used to associate each trip origin to a CBG and each trip destination to a CBG. If the origin and destination CBG were the same, that trip was removed from the study since intrazonal travel times were not modeled by the cube.

A similar set of methods were used when obtaining and prepping the 2011 UTA On-Board Survey. All of the trips that were taken by an individual under 18, that did not have a latitude or longitude for the origin or destination, that did not begin or end in the study area, or that did not have a trip time associated with them were removed from the analysis. Unfortunately, unlike the Utah Household Travel Survey data, this survey did not record the date of the trip. However, a transit planner at the UTA stated that it is most likely that all of the trips occurred between Monday–Thursday, so therefore it was assumed that all of the trips that occurred were performed on a weekday. Again, using the latitude and longitude information, each trip's origin and destination were associated with the CBG in which it was located. If the origin and destination CBG of a trip were the same, they were removed from the analysis.

Both of the surveys were processed in a similar fashion. First, an origin/destination ID was generated in order to associate the trip with the cube results. To determine the transit travel time for each particular trip, the cube was used based on the time that trip was taken. However, to avoid confusing trips where the individual might have barely missed the bus, train, etc. as times when the transit travel times were above average, an average travel time was generated based on all the travel times that occurred 30 minutes prior to, and 30 minutes after the trip was actually taken (1-hour window). The average travel time within this window was used in place of the specific minute-based travel time. Lastly, a customized *Python* script was created that automatically determined which OD pair the trip belonged to, the time that the trip occurred, and the average travel time within 30 minutes of the actual trip time.

The average transit travel time for each OD pair across the entire day was calculated to examine the difference between the actual OD travel time of the trip compared to the average OD travel time for that day. In addition, the daily standard deviation for the OD pair was calculated. Using these data, a Z-score was computed to determine to which degree a trip was taken at a time that was shorter or longer than the average transit trip time for the entire day. The z-score is defined as

$$Z_{ijm} = \frac{T_{ijm} - \bar{T}_{ij}}{\sigma_{ij}}$$

where T_{ijm} is the actual travel time from i to j at time m, $\bar{T}_{ij}$ is the mean travel time (between 5am and 10pm) from i to j, and σ_{ij} is the standard deviation of the travel times (between 5am and 10pm) from *i* to *j*.

If any of the trips had a standard deviation of 0, likely because walking from the origin to the destination was the fastest method, they were also discarded. For the UTA on-board survey, the same method was used to calculate the Z-score of the return trip.

Once both of the travel surveys were prepped, they were analyzed to compare how the public transit network adequately supplied access at the times that different sociodemographic groups tend to travel using the Z-scores from the trips. For each survey, a selection of demographic factors were chosen, with Tables 5 and 6 highlighting these factors. The first part of the analysis involved using the *R statistical software* package to perform an ANOVA to check if significant differences between social groups existed.

Table 5: Utah Household Travel Survey factors of interest.

Age	18–24; 25–34; 35–44; 45–54; 55–64; 65–74, 75–84, 85 +
Trip Purpose	HBO, HBPb, HBSch, HBShp, HBW, NHBW, NHWNW
Peak Travel	Off-peak; Peak
Gender	Female; Male
Employment	Full-time; Homemaker; Not-employed; Part-time; Retired; Self-employed; Student (25 or Less); Student (employed)
Education	Associates; Bachelors; Graduate Degree; HS Diploma; Less than HS; Some College; Technical
Hispanic	Hispanic; Not-Hispanic; N/A
Race	Other Race; White; N/A
Licensed	Licensed; Not Licensed
Lmtd. Mobility	Limited Mobility; No Limited Mobility; N/A
Hshld. Income	Under 10k; 10k–25k; 25k–35k; 35k–50k; 50k–75k; 75k–100k; 100k–150k; 150k–200k; 200k–250k; Over 250k; N/A
Years/Res.	> 1; 1–5; 6–10; 11–15; 16–20; < 20
Place Type	Downtown; Residential; Small Town; Suburbs (Houses); Suburbs (Mix)
Res. Type	> 3 Apts.; < 4 Apts.; Dorm; Mobile; Multifamily; Single Family; Townhouse

Table 6: UTA On-Board Survey factors of interest.

Primary Mode	Bus; FrontRunner; TRAX; N/A
Fare Type	Adult; Cash; Day/Group; Discounted; Ed/Eco/Annual; Free Fare; Medicaid; One-way; Reduced Fare; Senior; Student
Ingress Mode	Bike; Drove; Walk
Egress Mode	Bike; Drove; Walk
Frequency	First Time; Less than 1 / Week; 1 Day; 2 Days; 3 Days; 4 Days; 5 Days; 6 Days; 7 Days
Household Vehicles	None; 1 Vehicle; 2 Vehicles; 3 Vehicles; 4+ Vehicles
Drivers Licensed	Licensed; Not Licensed
Age	18–24; 25–44; 45–64; 65 +
Gender	Female; Male
Income	Less than 15k; 15k–25k; 25k–35k; 35k–50k; 50k–75k; Over 75k; N/A
Purpose	HBC; HBO; HWB; NHB

4. RESULTS AND DISCUSSION

The results of the analysis are explored and discussed in this section. First, the results of the cube for the whole study area and comparing how the public transit travel times are affected by distances are examined. This is followed by exploring the outcome of the analysis of the public transit network in regards to specific origins and destinations of interest and how the accessibility to these locations is different for the sociodemographic groups of interest. Lastly, the results from determining how well the public transit network supplied service for the travel demand of the different sociodemographic groups using the individual travel surveys is highlighted.

4.1 Entire Study Area (Wasatch Front) Travel Time Analysis

As mentioned, prior to examining specific destinations, the entire study area was first analyzed to highlight any overall patterns that might be present.

4.1.1 Holistic Analysis of Travel Times, Ranges, and Speeds

The transit travel time results from the cube were used to analyze the fluctuations in the public transit network throughout a weekday, Saturday, and Sunday. First, two different charts were generated that depict several summary statistics for each of the days being studied. These summary statistics are comprised of the results from all of the origins to all of the destinations as a way to quickly examine the overall fluctuations in the public transit network. Next, a series of maps highlight the spatial component of some of the various statistics, such as travel time and travel speed, and how they relate from each CBG to all other CBGs in the study area.

As Figure 10 indicates, the average travel time for the entire study area on a weekday was around 150 minutes. The average travel time on Saturday was fairly similar, at around 175 minutes. However, the average travel time for Sunday was very different being close to 300 minutes. Figure 11 (left) indicates that the average travel speed for the entire study area on a weekday was around 9 miles per hour, with Saturday being slightly less, at just a little over 8 miles per hour. However, Sunday's average speed was around 5.25 miles per hour, much slower than that of a weekday or Saturday. Figure 11 (right) also highlights that the average travel time range (maximum travel time minus minimum travel time) for a weekday was around 50 minutes, with Saturday slightly higher at around 55 minutes. This indicates that the fluctuations in travel time for the OD pairs were fairly similar for a weekday and Saturday. However, higher fluctuations are shown to occur on Sunday, with the average being around 70 minutes.

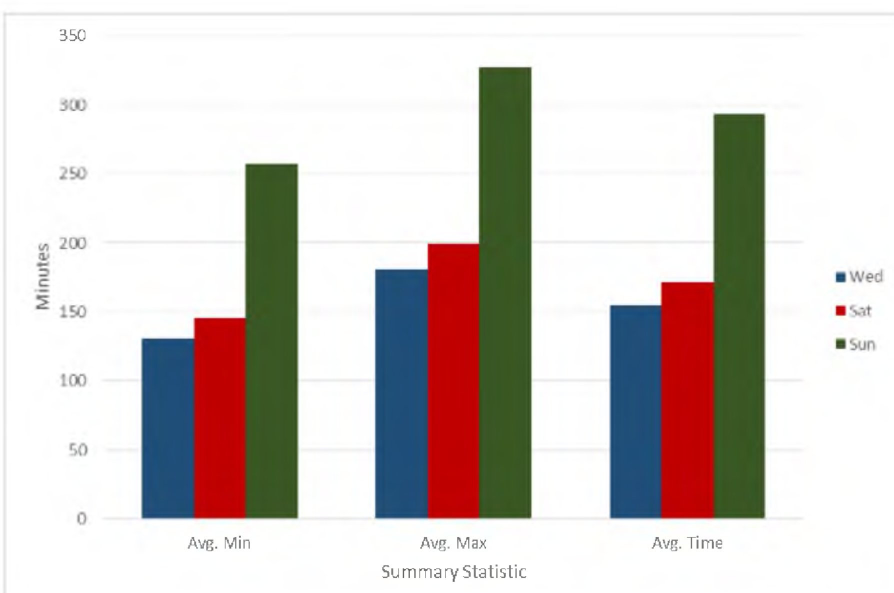


Figure 10: Travel time min, max, and avg. for each type of day.

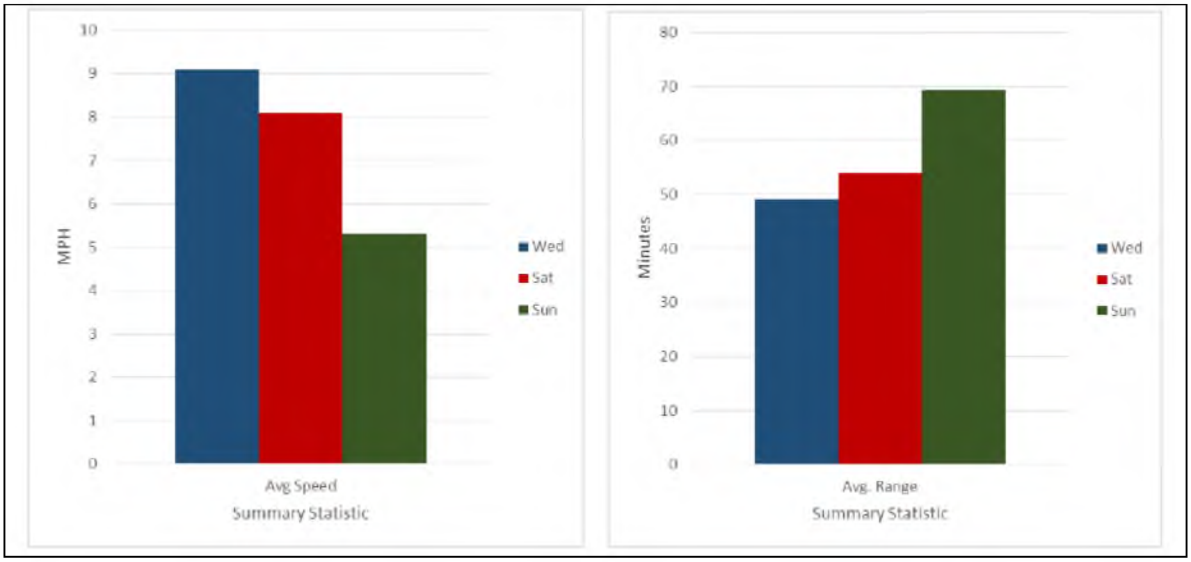


Figure 11: Travel speed and travel time range for each type of day.

Examining the maps (Figures 12 and 13) helped first to highlight the overall spatial patterns in travel times and travel speeds. Overall, the lower travel times tended to be locateded in the center portion of the study area (Figure 12). Due to the abundance of the origins and destinations in this area, that would be expected. Similarly, the outer reaches of the study area, especially the northern and southern areas, had the highest travel times due to the geographic distance from the center of the study area. Lastly for the travel times, a north-south directional trend was noticed, with lower travel times further north and south of the central study area, but higher travel times when examining similar distances to the east and west.

Figure 13 of travel speeds depicts a different trend. While the central study area had the lowest travel times, it also had the lowest travel speeds due to the reliance on walking and bus routes. As an exception, the areas in the central part of the study area that were serviced by TRAX and FrontRunner attained higher travel speeds. Another difference noticed between the travel times and travel speeds was that the northern and

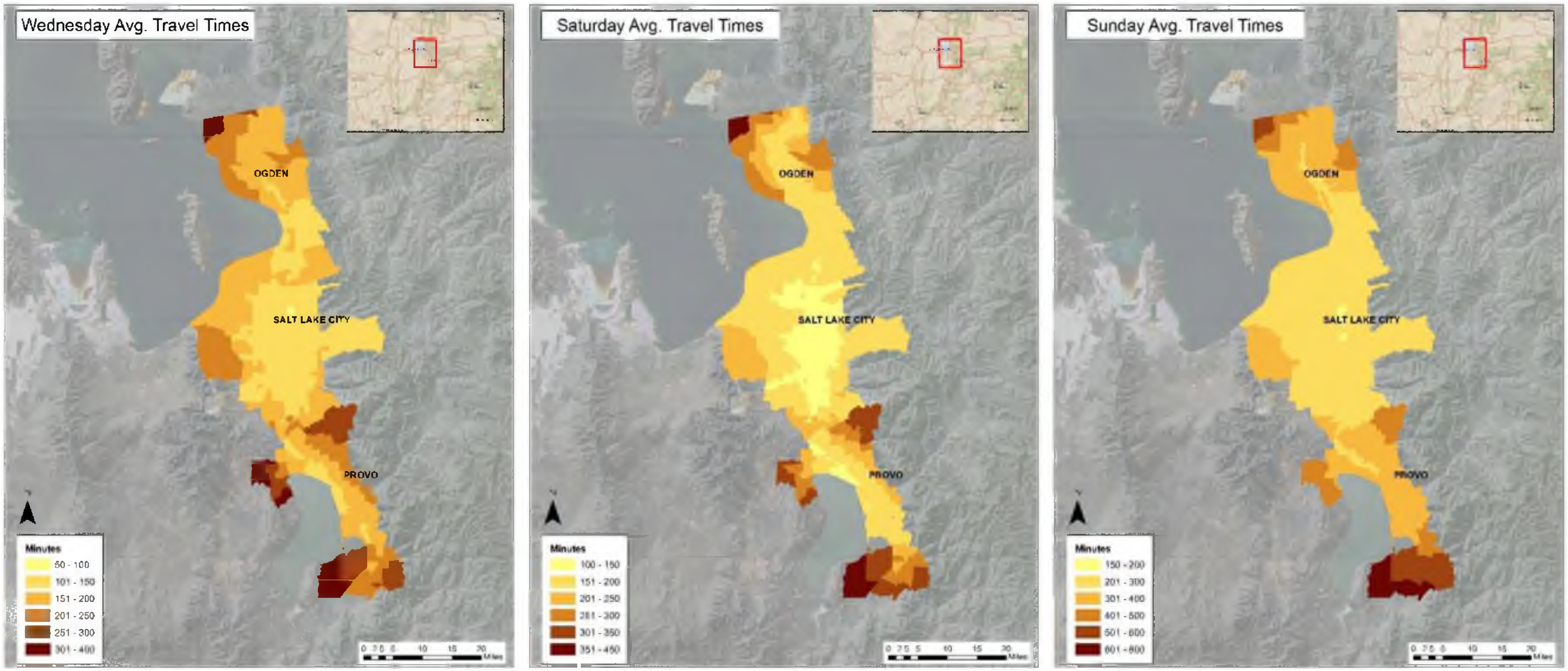


Figure 12: Avg. travel times for weekday (left), Saturday (middle), and Sunday (right) from each origin to all destinations.

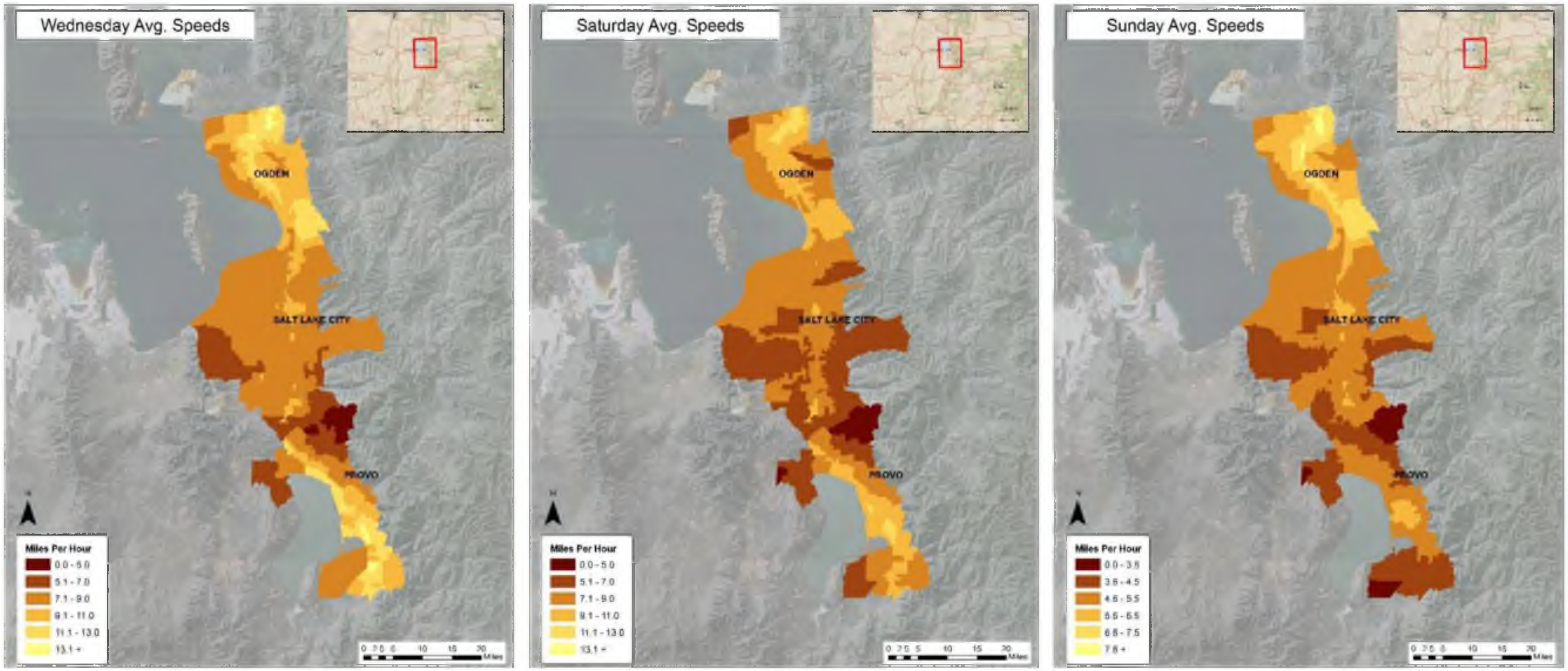


Figure 13: Avg. travel speeds for weekday (left), Saturday (middle), and Sunday (right) from each origin to all destinations.

southern portions of the study area actually had the highest travel speeds due to routes from these locations using FrontRunner service. While the travel times can measure the costs of transit travel, since they are highly dependent on travel distance, they are not as suitable as travel speeds for indicating the transit agency's level of service provision. As the maps in Figure 13 show, higher travel speeds tended to be provided by FrontRunner and TRAX services. The latter caused the higher travel speed islands located throughout the valley.

In addition to examining and comparing the average overall travel times and speeds for the 3 days, simple graphs were generated in order to better visualize how the average travel time, travel time range, and travel speeds for each of these days fluctuated throughout the day (Figure 14). The charts visualize the time period from 6am to 6pm, with patterns beyond these points solely caused by ramping up and ramping down of overall service at the day's beginning and end.

The charts in Figure 14 show that the transit network appeared to begin operation earlier in the day on the weekdays. However, Saturday appeared to end operation later in the evening. In general, Sunday operation appeared to start later in the day (similar to Saturday), but decreased operations earlier in the evening.

While the travel times and speeds were smoothed for each hour losing the complete fluctuations that were occurring during that hour, the averages still allowed to examine the overall fluctuation trends throughout the day. In addition, while the travel times and speeds were of importance, the levels of fluctuation were the main focus of this research and examining how the travel times fluctuated on average across the day helped to better capture this. As Figure 14 (middle) shows, for a weekday, around 6 in the

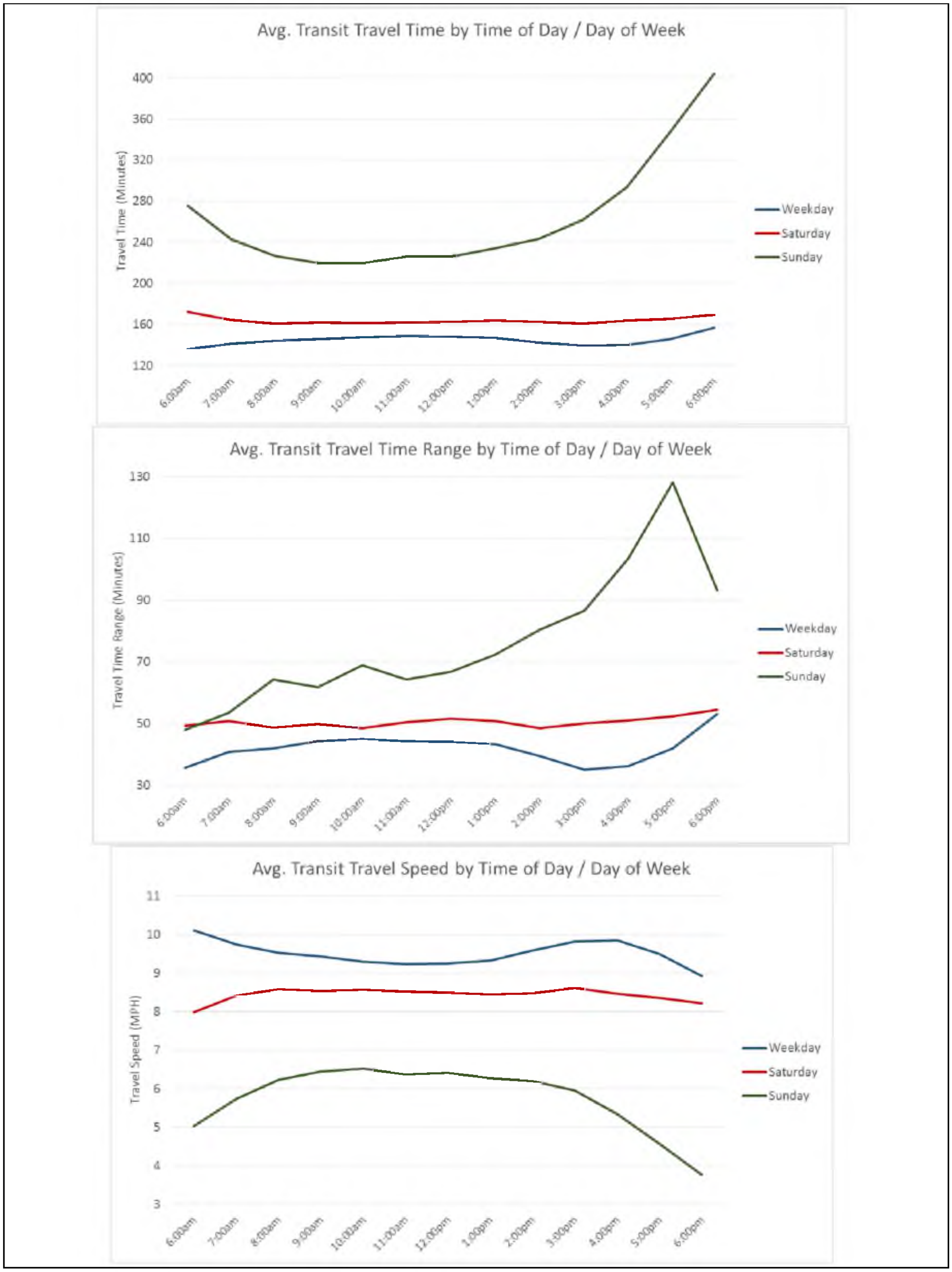


Figure 14: Travel time, range, and speed fluctuations across each type of day.

morning the ranges were fairly low on average. As the day progressed, the travel time ranges slowly increased until around 11am or 12pm when they began to decline again. A deep decline in ranges occurred around 3 and 4pm before they increased. Saturday was slightly different, with increases and decreases in the travel range as the day progressed. Lastly, Sunday was fairly different, starting the day with the lowest ranges and continually increasing as the day progressed before decreasing around 5pm. These findings indicate that overall in the whole study area, regardless of the day, the lower travel times and higher travel speeds tended to be during the morning and evening rush-hour periods, with higher travel times and lower travel speeds noticed during the midday. When examining the travel times ranges, a similar pattern was noticed. The most consistent service and less fluctuation in travel time occurred during the morning and evening, with the most fluctuation and inconsistent service throughout the rest of the day.

4.1.2 Holistic Analysis of Isotropic and Anisotropic Travel Times

Once the overall fluctuations in the transit network were examined for the entire study area, the effects of distance (Euclidean, vertical, and horizontal) on the different summary statistics were explored. First, the effects of Euclidean distance on average travel time, average travel time range, average travel time standard deviation, and average travel speed were examined. Figure 15 examines the relationship between Euclidean distance and travel time and speed, while Table 7 contains OLS regression results including the slope, intercept, and p-value for these same statistics. Similarly, Figure 16 examines the relationship between Euclidean distance and travel time range, with Table 8 containing the OLS regression results for this statistic. In these regressions, Euclidean distance between origin and destinations in the cube was taken as the

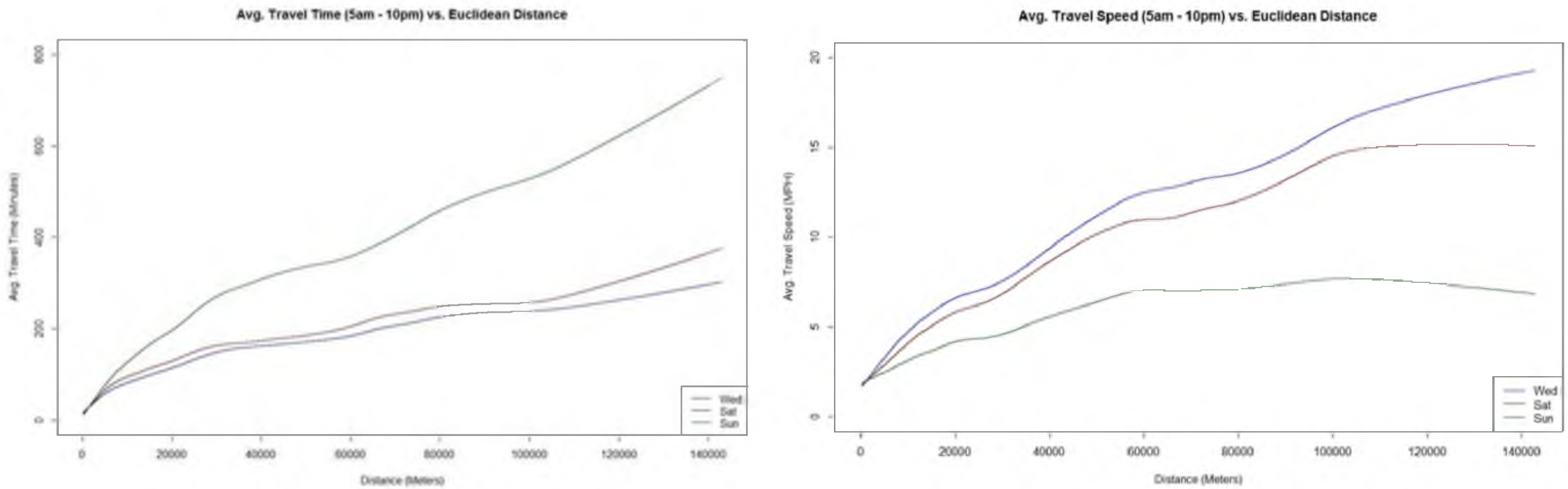


Figure 15: Avg. travel time (left) and travel speed (right).

Table 7: Travel Time (A) and Travel Speed (B)—Euclidean Distance.

(A)	*Intcpt. (min)*	*Slope (min/m)*	*Slope (min/km)*	*Slope P-Value*
Wed	78.24	0.002	2	<2e-16 ***
Sat	86.5	0.002	2	<2e-16 ***
Sun	96.95	0.005	5	<2e-16 ***

(B)	*Intcpt. (min)*	*Slope (MPH/m)*	*Slope (MPH/km)*	*Slope P-Value*
Wed	3.81	0.0001	0.1	<2e-16 ***
Sat	3.39	0.0001	0.1	<2e-16 ***
Sun	3.1	0.00005	0.05	<2e-16 ***

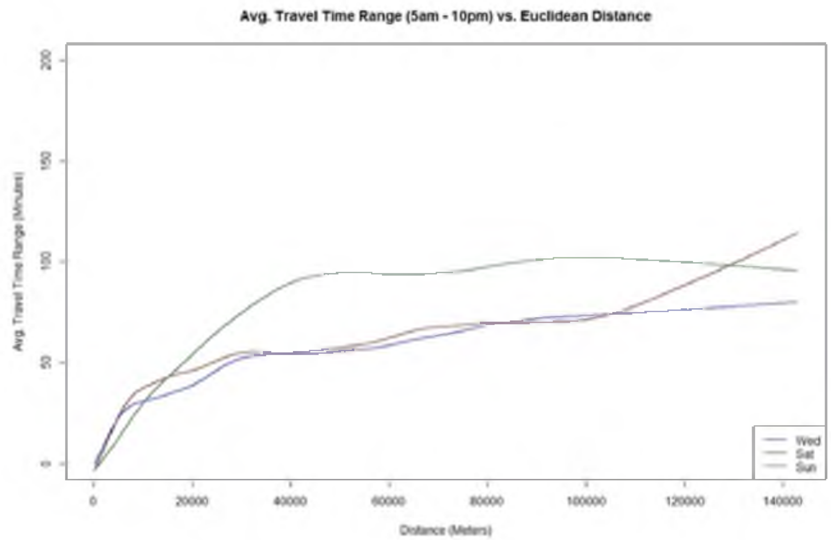


Figure 16: Avg. travel time range.

Table 8: Travel Time Range—Euclidean Distance.

	Intcpt. (min)	*Slope (min/m)*	*Slope (min/km)*	*Slope P-Value*
Wed	28.9	0.0005	5	<2e-16 ***
Sat	32.96	0.0005	5	<2e-16 ***
Sun	32.58	0.0009	9	<2e-16 ***

independent variable, and the travel summary statistic (time, speed, range, etc.) was taken as the dependent.

First, examining Figure 15 (left) and Table 7A highlighted similar findings as previously stated, that the average travel times on a weekday and Saturday were fairly similar (2 min/km), with Sunday's average travel times increasing much more rapidly (5 min/km) as the distance increased. However, all 3 days showed a similar pattern, with a steep increase in average travel times within the first kilometer before transitioning to a more gradual increase as the distance increased. It was expected that for this first kilometer distance in OD pairs, walking was the fastest mode of transportation and therefore was the cause of this step increase. However, the more gradual increase after 1 kilometer was most likely the result of public transit providing faster velocity travel. The main reason that Sunday increased at a much more rapid pace is that on a weekday and Saturday, these longer distanced OD pairs could rely on the FrontRunner commuter train and as a result keep the travel time fairly low. However, the FrontRunner service, at the time of analysis, did not operate on Sundays, and therefore much slower modes of transit needed to be utilized to commute between those longer spaced OD pairs. Figure 15 (right) and Table 7B highlights how the travel speed varied across Euclidean distance. These graphs show a similar finding with that of travel time, with the weekday and Saturday actually increasing in travel speed as the distance increased at a fairly good degree (0.1 MPH/km).

However, Sunday tended to increase a little more gradually (0.05 MPH/km) before eventually leveling off and even decreasing, with FrontRunner (by far the fastest mode due to fewer stops and the train's ability for higher speeds) likely the reason for this gradual increase. Therefore, the OD pairs of the longest distances tended to rely on FrontRunner the most. As a result, the farther distanced OD pairs were able to travel quicker on weekdays and Saturday. As mentioned though, FrontRunner service did not operate on Sundays, which could be seen by the leveling out and eventual decline in speeds as the distance increased.

Figure 16 and Table 8 examine how travel time range varied based on distance. Figure 16 highlights that similar patterns were exhibited when comparing the different days of the week, with a steep increase in the travel time range before a more gradual increase after the first kilometer. In addition, the weekday and Saturday had similar slopes (5 min/km), with Sunday again increasing more at 9 min/km. However, Figure 16 also highlights that the overall trend in travel time range for the weekday and Saturday increased as the distance increased, while for Sunday the travel time range increased very rapidly at first prior to becoming more constant. This is understandable given that the weekday and Saturday typically had more trip options throughout the day, and therefore much more fluctuation on travel times, while for Sunday very few options were available resulting in little fluctuation in travel times (as all trips take similar times).

Examining how the different statistics varied over Euclidean distance helped to explain how travel times and travel speeds fluctuated as distance increased. However, because the farthest apart OD pairs located in the study area were positioned vertically (north to south) and the infrastructure for FrontRunner and TRAX were almost entirely oriented in a north-south direction, it was necessary to explore if the travel times and travel speeds were isotropic or anisotropic by comparing similarly distanced OD pairs both vertically (north to south) and horizontally (east to west) in the study area. Figures 17–24 depict charts that highlight how the travel time varied vertically and horizontally for different distance groups in the study area. Because travel speed and travel time range exhibited similar patterns as the travel time, they were excluded from the discussion.

When comparing horizontal to vertical OD pairs that ranged between 2 and 4 kilometers (Figure 17), it was seen that horizontal (east-west) OD pairs took longer to travel between than those of similar distance that were vertical (north-south). For example, the vertical weekday ranged between 2 and 5 minutes faster than the horizontal. The slopes also helped to illustrate this, with the vertical slopes being about 1 min/km lower than the horizontal ones.

When comparing horizontal to vertical OD pairs that ranged between 4 and 6 kilometers (Figure 18), a similar pattern was seen, with the horizontal OD pairs taking

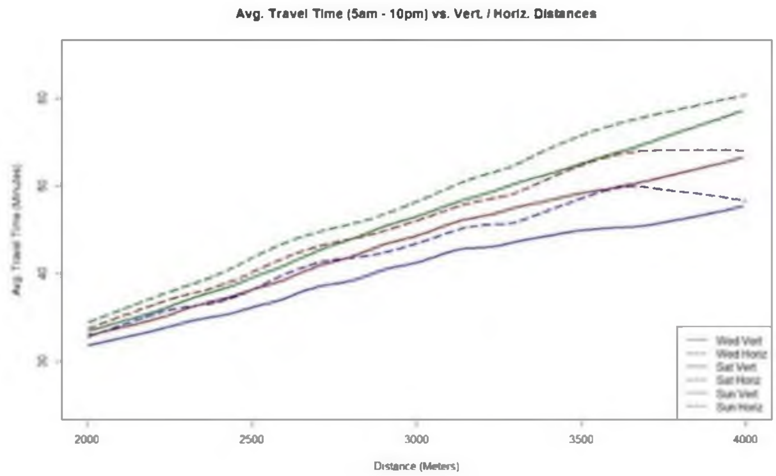


Figure 17: Avg. travel time for OD distances between 2k–4k meters.

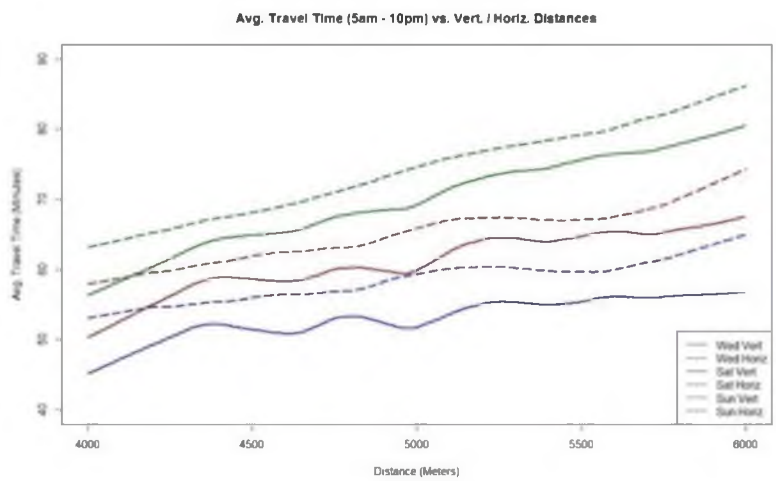


Figure 18: Avg. travel time for OD distances between 4k–6k meters.

longer than the vertical OD pairs. However, the gap between the horizontal and vertical pairs continued to widen, with the vertical pairs being around 5 to 10 minutes faster. By contrast, though, except for Sunday, the slopes were fairly close together, at around 6 min/km (with Sunday being much higher at 11 min/km). In addition, it was seen that more fluctuation was present in the vertical distances compared to the horizontal ones.

When comparing horizontal to vertical OD pairs that ranged between 6 and 8 kilometers (Figure 19) and 8 and 10 kilometers (Figure 20), the horizontal pairs

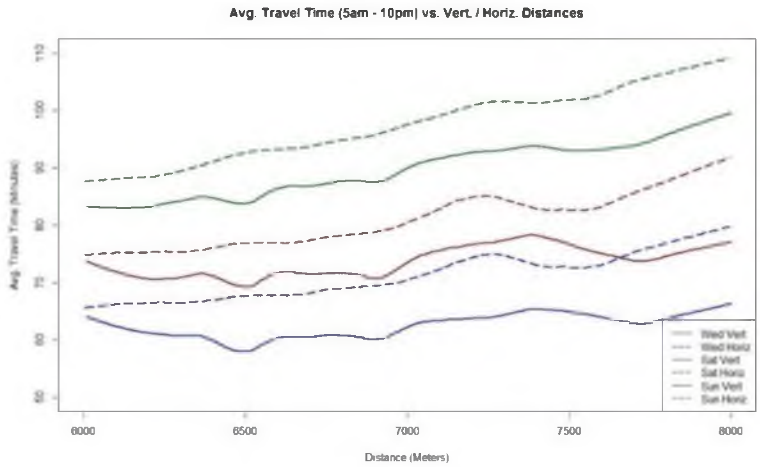


Figure 19: Avg. travel time for OD distances between 6k–8k meters.

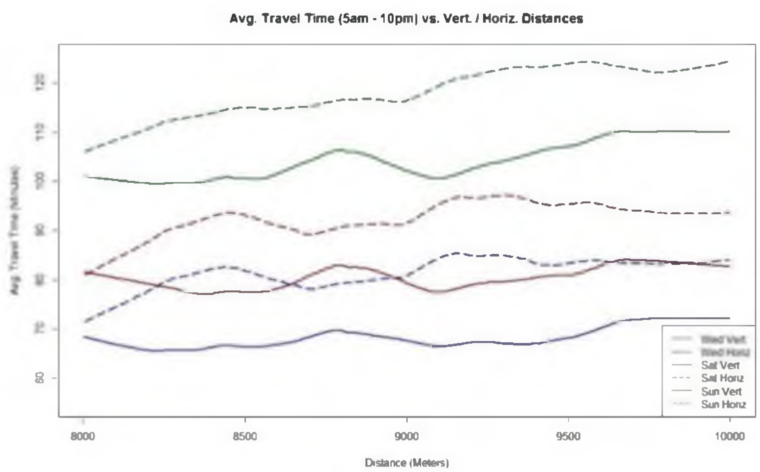


Figure 20: Avg. travel time for distances between 8k–10k meters.

continued to take longer than the vertical pairs, with the vertical pairs again being about 5–10 minutes faster than the horizontal pairs between 6 and 8 kilometers and becoming about 10–15 minutes faster between 8 to 10 kilometers. The slopes were fairly close together for the weekday and Saturday, with a 1 min/km difference in slope, with even lower changes for the 8 and 10K, being less than 1 min/km. For Sunday, the differences were still around 2 min/km. Also, again it was seen that slightly more fluctuation was present in the vertical distances compared to the horizontal ones. In Figure 21, between

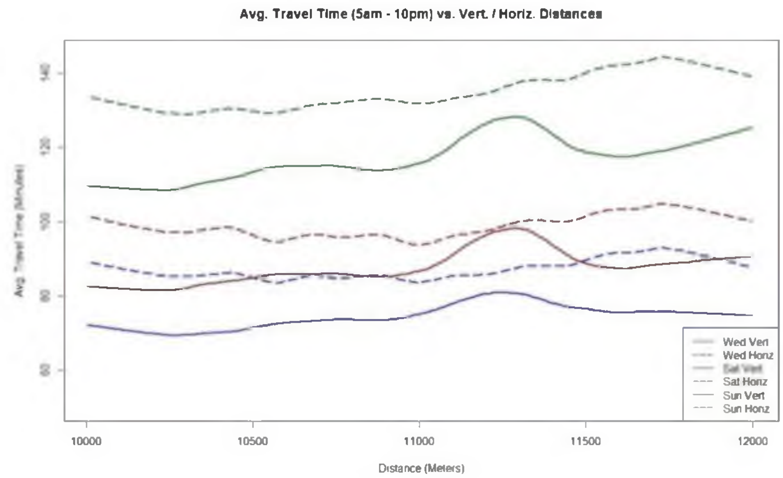


Figure 21: Avg. travel time for OD distances between 10k–12k meters.

10 and 12 kilometers the gap continued to become even wider, with the vertical travel times becoming around 15 to 20 minutes faster than the horizontal travel times. In addition, at this point the increases in travel times with distance began to even themselves out, with a slope for the weekday vertical trips going from 8 min/km for 2 to 4 kilometers, to 5 min/km for the 10 to 12 kilometer distances. However, while the weekday and Saturday were around 5 min/km, Sunday had a slightly higher slope of 8 min/km.

From 12 to 20 kilometers (Figures 22–24), differences began to become evident. While for Sunday, the vertical pairs still continued to exhibit lower travel times than the horizontal pairs, and the travel times for the weekend and Saturday began to converge for the vertical and horizontal pairs, with various times where the horizontal travel times were actually shorter than the vertical (predominantly seen in Figures 23 and 24). While this dramatic difference may have been caused for different reasons, the main reasoning was most likely the result of the location of the TRAX light-rail lines. Most of the small east-west distances in Salt Lake City relied on a combination of bus and TRAX.

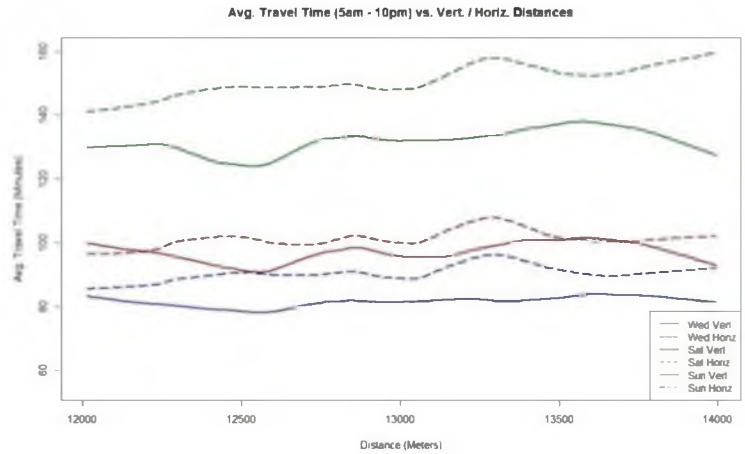


Figure 22: Avg. travel time for OD distances between 12k–14k meters.

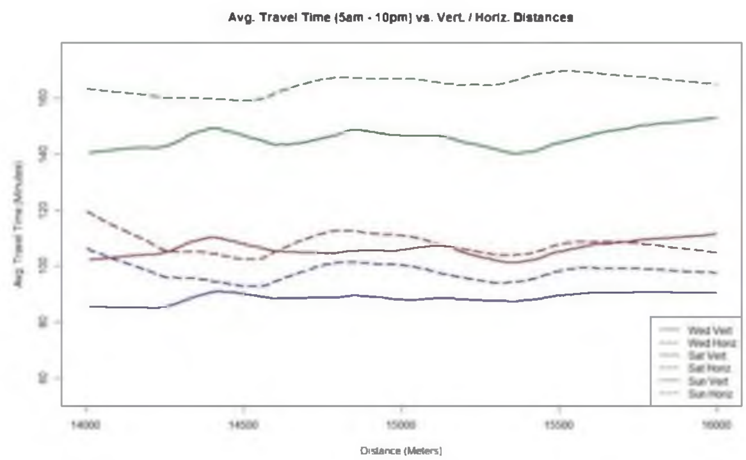


Figure 23: Avg. travel time for OD distances between 14k–16k meters.

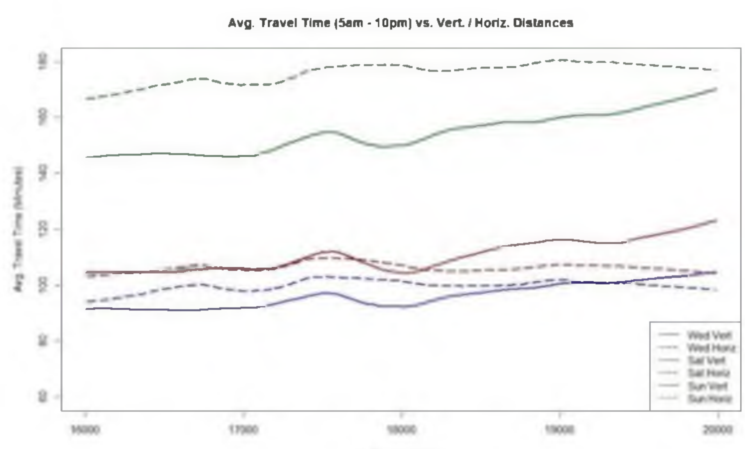


Figure 24: Avg. travel time for OD distances between 16k–20k meters.

However, the smaller east-west trips near Ogden and Provo could only rely on bus trips. The small north-south distances could take full advantage of TRAX due to its more dominant north-south structure. However, the longer east-west trips could rely more on TRAX (as those longer horizontal OD pairs were predominantly located around Salt Lake City), especially from the University of Utah to downtown or the airport. However, CBGs positioned vertically were typically located east of TRAX and FrontRunner near Salt Lake City and away from TRAX and FrontRunner altogether near Ogden and Provo. As a result, these OD pairs relied on buses to travel. Therefore, for the longer distances, travel times tended to be similar for the vertical and horizontal distances.

The results have concluded that travel times are anisotropic in the study area. This was important because a majority of the Hispanic and non-White population live in the western portion of the study area. As a result of this, these minority groups must travel west to east to get to most locations (even if they eventually travel north or south to destinations), and then east to west to arrive back at home. Because of this, those that require the service to get to locations mainly north or south of where they live had lower travel times and higher travel speeds than those that must travel east-west or west-east, especially the Hispanic or non-White population.

4.2 Specific Origins/Destinations Analysis

While examining the average travel times and speeds for all of the origins to all of the destinations allowed for a better understanding of the spatial patterns and aggregate levels of accessibility, examining how travel times and speeds varied from all of the origins to a specific destination allowed for a better look at how well certain destinations could be accessed, such as education, healthcare, and employment facilities. This section proceeds by examining how travel times and travel speeds to specific destination fluctuated over time and space. Then, the travel times between several specific OD pairs were examined. Lastly, sociodemographic factors for each CBG were explored, with weighted travel time averages being calculated to a selection of the specific destinations that had been chosen to examine more closely. Figure 5 depicts the study area and illustrates the specific locations that were chosen for this analysis.

4.2.1 Specific Destinations Travel Time Analysis

Following is a series of figures that depict how travel times to specific destinations varied over space (maps) and time (charts) for weekdays and weekends. After each figure is a complementary table highlighting when travel times were highest and lowest. The destinations chosen for this analysis included the Salt Lake International Airport (Figure 25 and Table 9), the South Towne Shopping Center (Figure 26 and Table 10), the Intermountain Medical Center (Figure 27 and Table 11), and the Salt Lake City (SLC) Central Business District (Figure 28 and Table 12). Review of Figures 25–28 revealed that travel times to the destinations were often lower when coming from the north or south to the destinations, but higher when coming from the east or west. This was especially noticed when inspecting the maps for the Salt Lake International Airport (Figure 25), the South Towne Shopping Center (Figure 26), the Intermountain Medical Center (Figure 27), and the SLC Central Business District (Figure 28).

The results indicated that for all of the destinations (Figures 25–28 and Tables 9–12), the start time of the network on the weekday was before the start time of the network for Saturday or Sunday, which was likely a planned occurrence due to the fact that many individuals rely on public transit to commute to work. For the weekend days, Saturday's

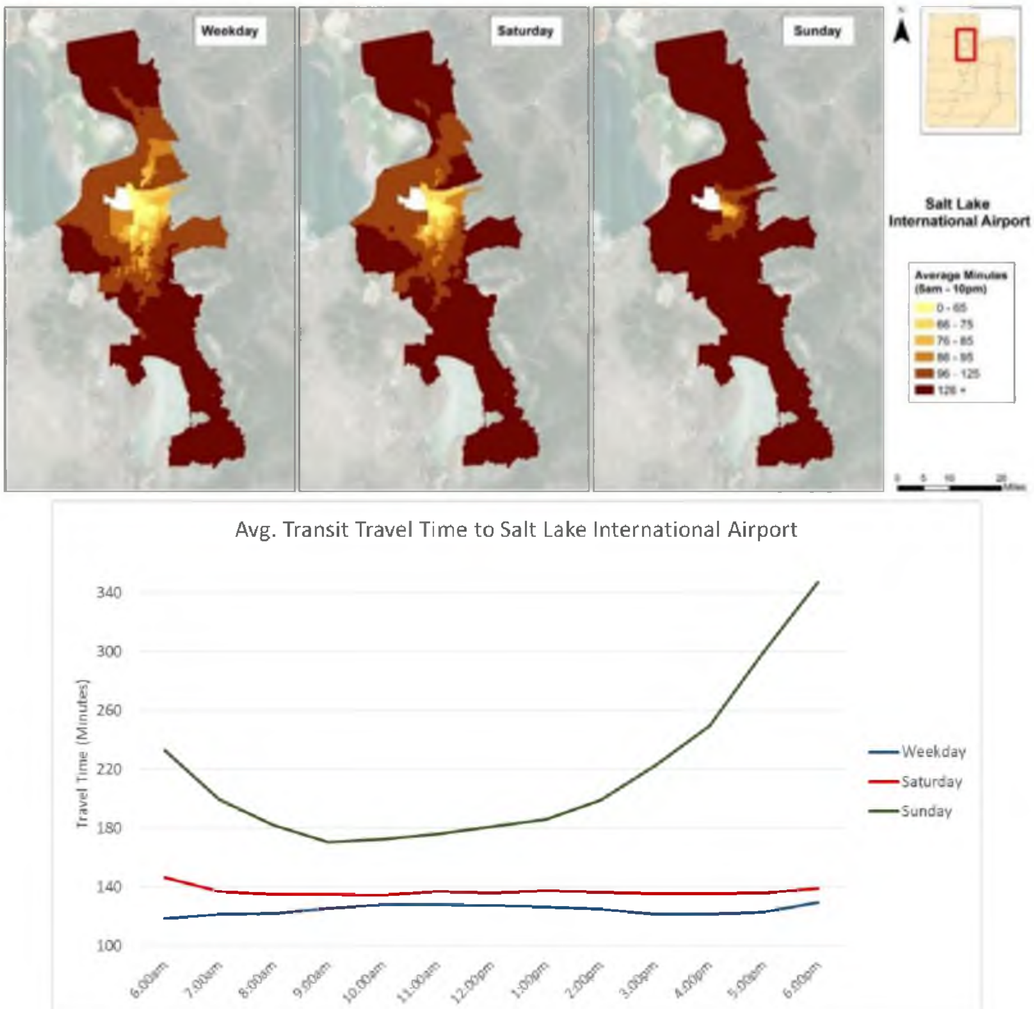


Figure 25: Salt Lake Intl' Airport travel times across space (top) and time (btm).

Table 9: High/low travel times for each day to the Salt Lake Intl' Airport.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am, 3–4pm	10am
Saturday	10–11am	12–1pm
Sunday	9am	1pm

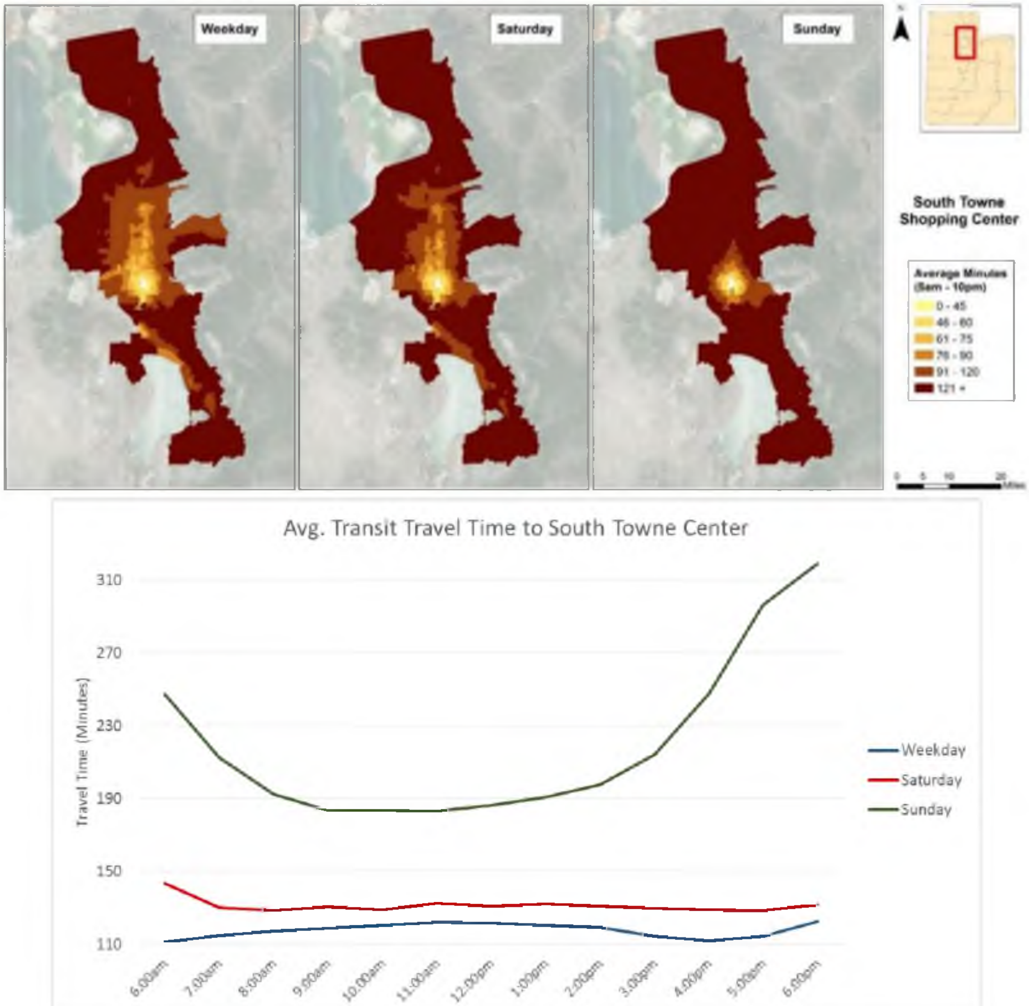


Figure 26: South Towne Center travel times across space (top) and time (btm).

Table 10: High/low travel times for each day to the South Towne Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am; 4pm	11am
Saturday	10am; 4pm	9am; 11am
Sunday	9am	2pm

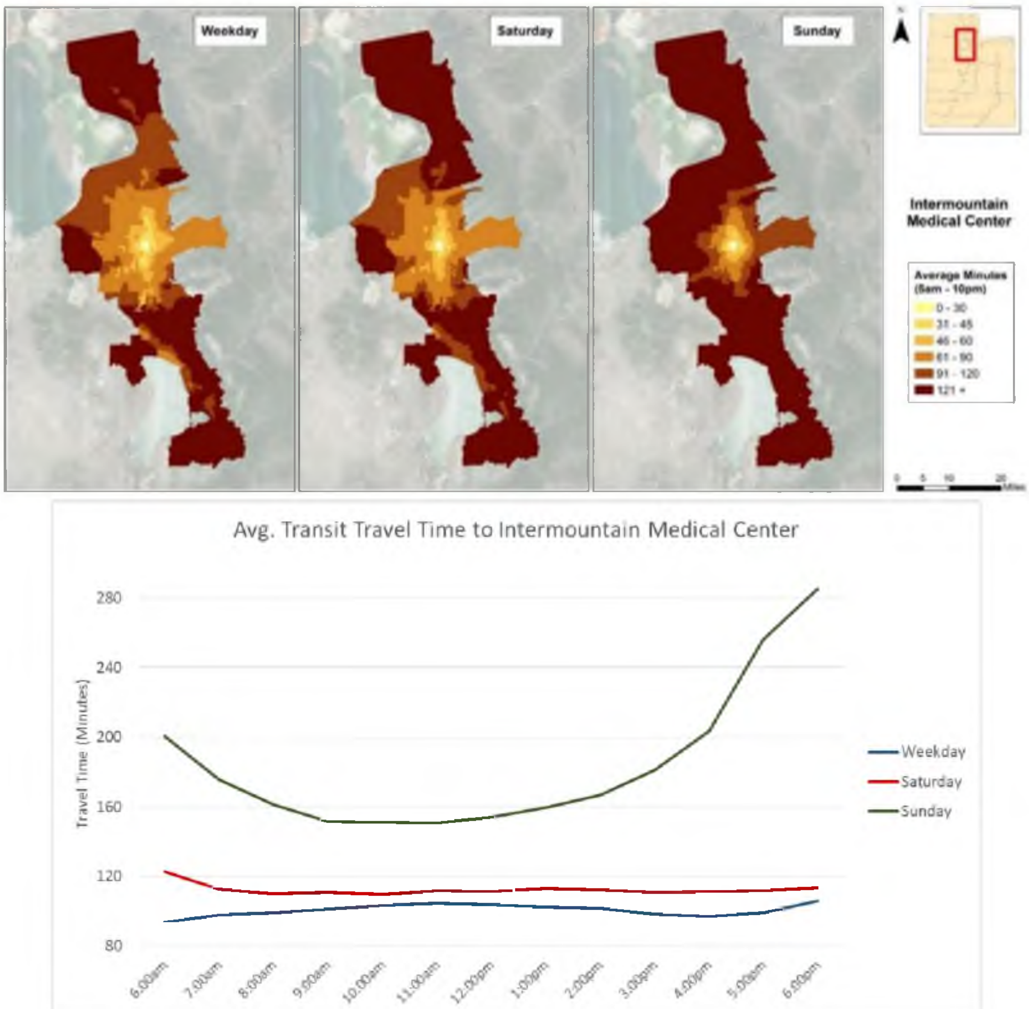


Figure 27: Intermountain Medical Center travel times across space (top) and time (btm).

Table 11: High/low travel times for each day to the Intermountain Medical Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am; 4pm	11am
Saturday	10am; 3pm	11am; 1pm
Sunday	9am	2pm

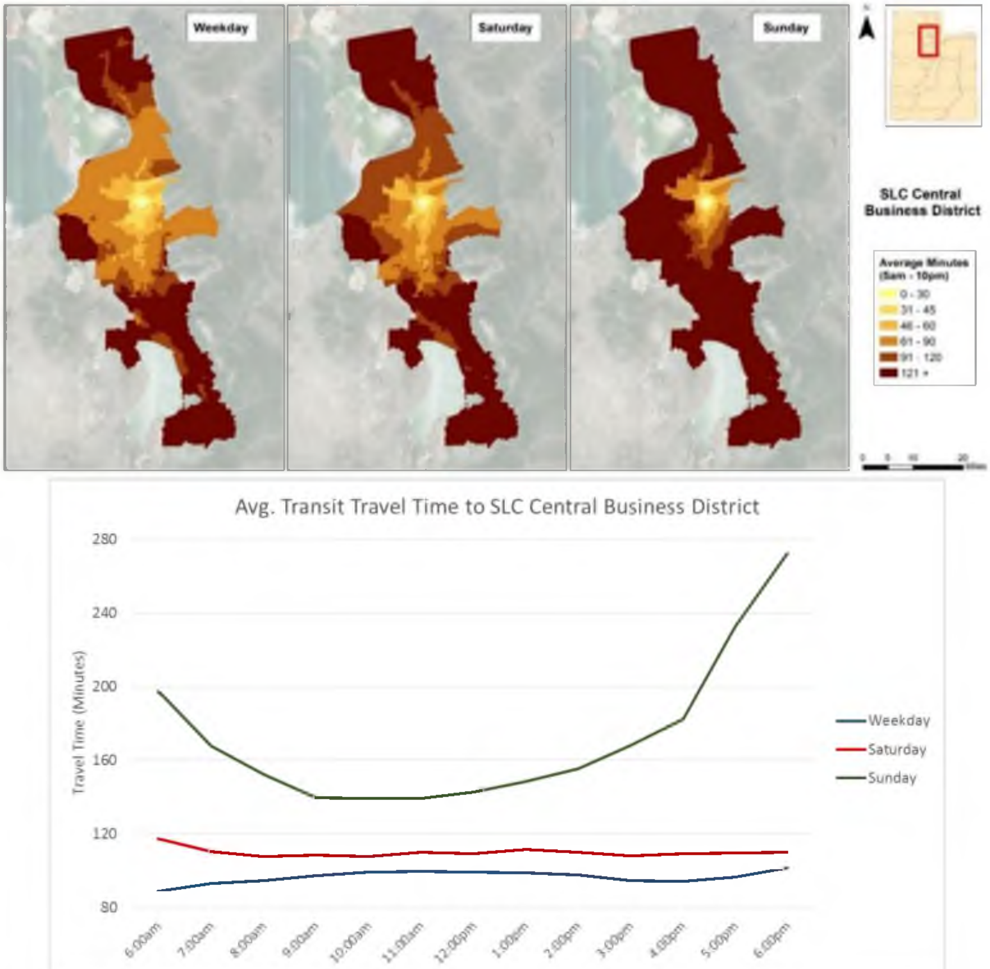


Figure 28: SLC Central Business District travel times across space (top) and time (btm).

Table 12: High/low travel times for each day to the SLC Central Business District.

	Low Travel Time Peaks	***High Travel Time Peaks***
Weekday	6am; 3–4pm	10–11am
Saturday	10am; 3pm	11am; 1pm
Sunday	9am	2pm

start time began later in the morning than the weekdays, but also earlier in the morning than Sundays, with all of the start times for Sunday being later in the morning than the weekday or Saturday and the ending times of the service earlier in the evening than for Wednesday and Saturday.

There are, however, other specific destinations that exhibited patterns that deviated from the typical overall patterns found in the destinations that were explored previously in Figures 25–28. For example, while service to the previous destinations (Figures 25–28) ended later on Saturday compared to the weekdays, for the University of Utah (Figure 29 and Table 13) and for the East Bay Technology Park (Figure 30 and Table 14), service ended around the same time on the weekdays and Saturdays. This seems a little peculiar since the East Bay Technology Park consists of a lot of employment locations that may not require Saturday evening service. However, it is also an area of shopping and restaurants that would benefit from the network operating later on a Saturday. Another example of deviation was Cottonwood Heights Technology Park (Figure 31 and Table 15), which had an ending service time on Saturday earlier in the evening than the weekday. However, because this location consists mostly of corporate offices and employment locations, this would seem reasonable.

The smoothing technique that was used to make the travel times more visually appealing across the day removed the minute-by-minute fluctuations, but there were still some noticeable temporal trends for the destinations. Some locations, such as the airport (Figure 25), SLC Central Business District (Figure 28), and East Bay Technology Park (Figure 30) did notice a few peaks through the days, typically in the morning, midday, and the evening.

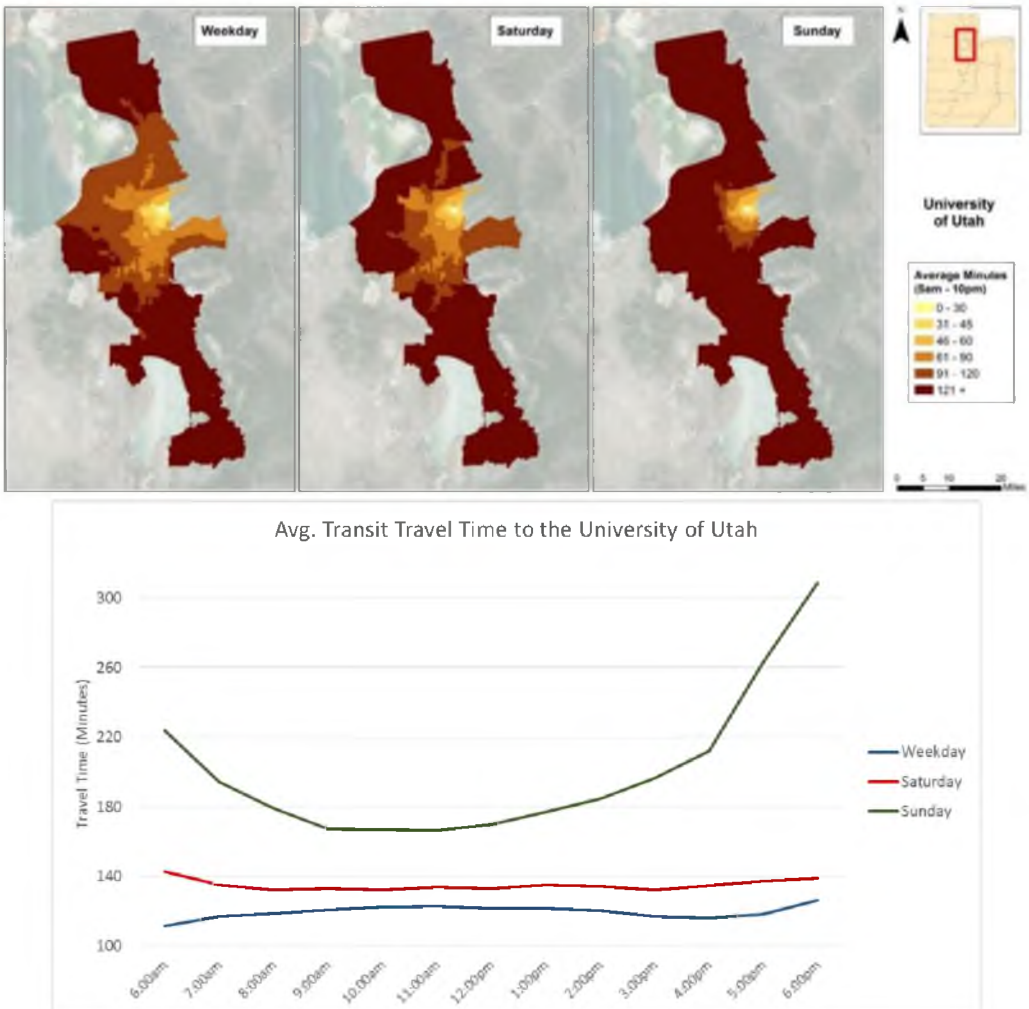


Figure 29: University of Utah travel times across space (top) and time (btm).

Table 13: High/low travel times for each day to the University of Utah.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am; 4pm	11am
Saturday	12pm; 3pm	11am; 1pm
Sunday	9am	2pm

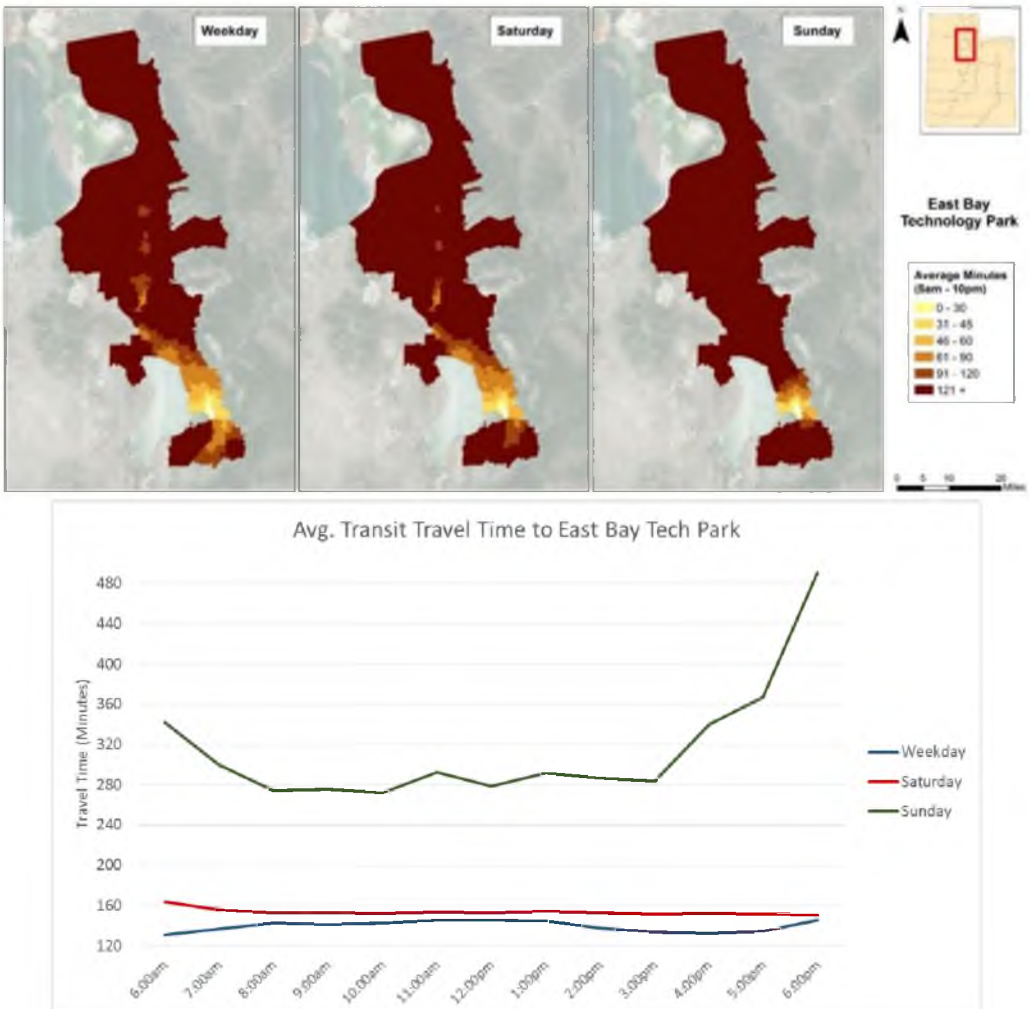


Figure 30: East Bay Tech Park travel times across space (top) and time (btm).

Table 14: High/low travel times for each day to the East Bay Tech Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am; 4pm	11am–1pm
Saturday	4–5pm	11am; 1pm
Sunday	9am	12–1pm

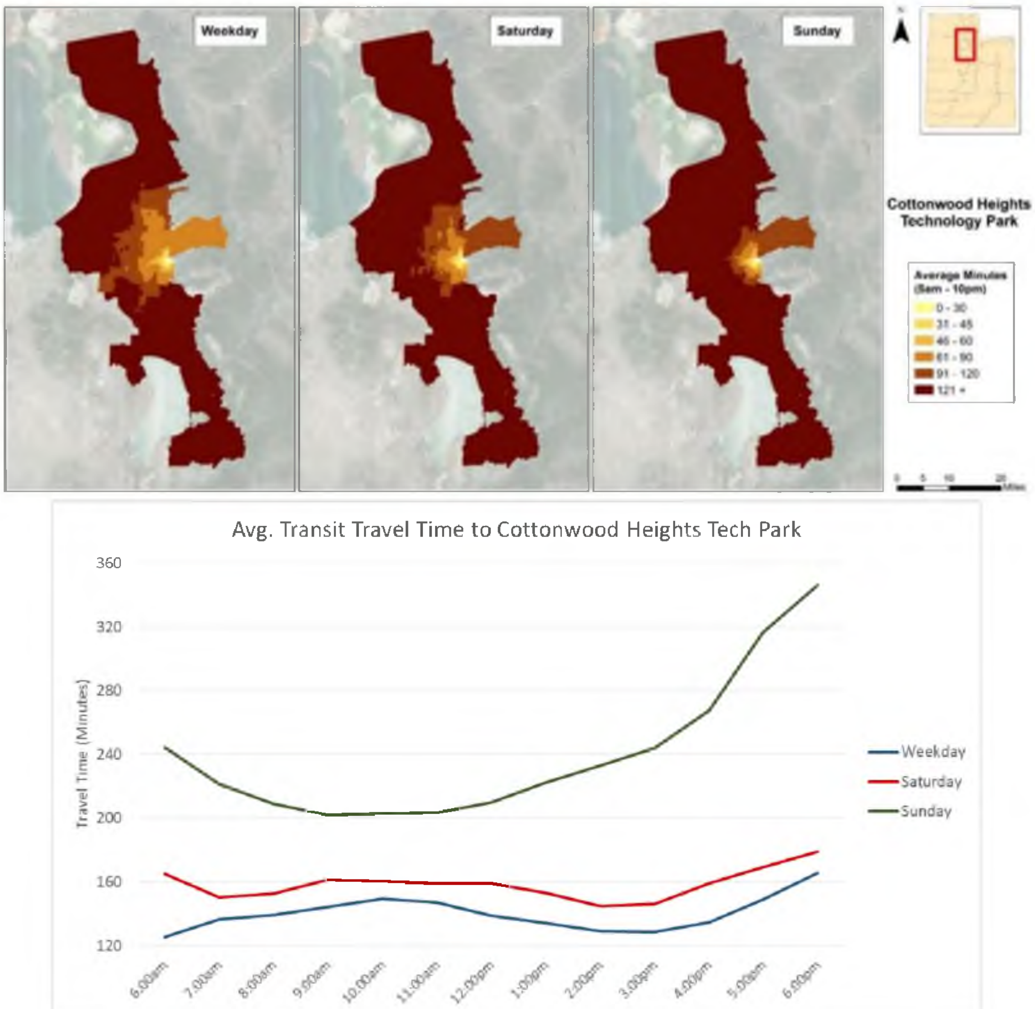


Figure 31: Cottonwood Heights Tech Park travel times across space (top) and time (btm).

Table 15: High/low travel times for each day to the Cottonwood Heights Tech Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am; 3pm	9am; 12pm
Saturday	7am; 2–3pm	11am; 1pm
Sunday	9am - 11am	2pm

As a result of this smoothing and because travel times from different destinations could be much higher or lower than other areas depending on their geographic location, it was decided that examining the travel time range to these destinations across the day would give a better understanding of the fluctuations that occur across the day. Several patterns emerged when examining the destinations. Some of the destinations, such as the Salt Lake International Airport (Figure 32 and Table 16), South Towne Shopping Center (Figure 33 and Table 17), and University of Utah (Figure 34 and Table 18) noticed more consistent ranges across the day with similar low or high ranges witnessed for several continuous hours.

By contrast, other destinations such as the SLC Central Business District (Figure 35 and Table 19), Cottonwood Heights Technology Park (Figure 36 and Table 20), East Bay Technology Park (Figure 37 and Table 21), and the Intermountain Medical Center (Figure 38 and Table 22) noticed distinct low or high ranges that occured only across a certain hour. In addition, across most of these destinations, the low and high ranges occurred around similar times. Most of the lower ranges, and therefore more consistent service and travel times, occurred either early morning, around 6am on a Weekday and Sunday, as well as around 4pm in the afternoon on a Weekday and Saturday. For the higher ranges, and therefore times with more fluctuation in service and travel times, these tended to occur during the late morning and early afternoon on the weekday and Saturday, mostly between 11am–1pm. In addition, higher ranges were also noticed around 5pm on Sundays. Some destinations did show differences from these patterns though. For example, the lower ranges to Cottonwood Heights Technology Park (Figure 36 and Table 20) tended to occur more in the early afternoon on the weekday and

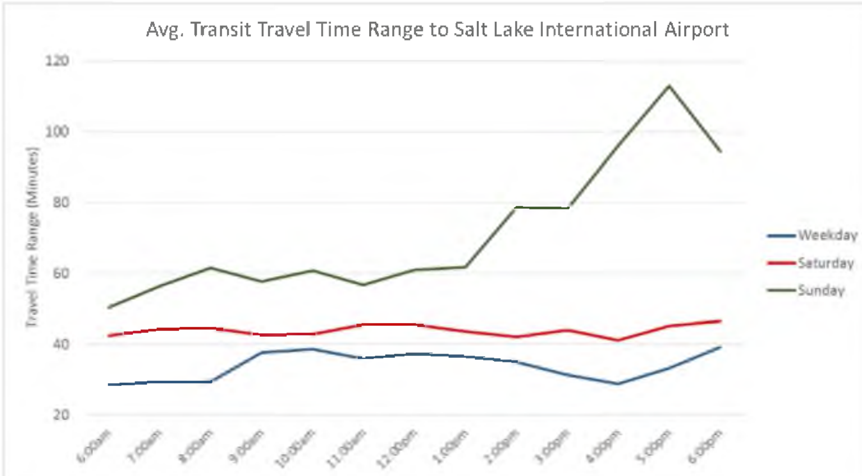


Figure 32: Salt Lake Intl' Airport travel time range across time.

Table 16: High/low travel time ranges for each day to Salt Lake Intl' Airport.

	Low Range Peaks	*High Range Peaks*
Weekday	6–8am; 4pm	9–10am
Saturday	4pm	12pm
Sunday	6am	5pm

Figure 33: South Towne Center travel time range across time.

Table 17: High/low travel time ranges for each day to South Towne Center.

	Low Range Peaks	*High Range Peaks*
Weekday	3–4pm	10am
Saturday	2pm; 4pm	11am
Sunday	9am; 11am	8am; 12–2pm

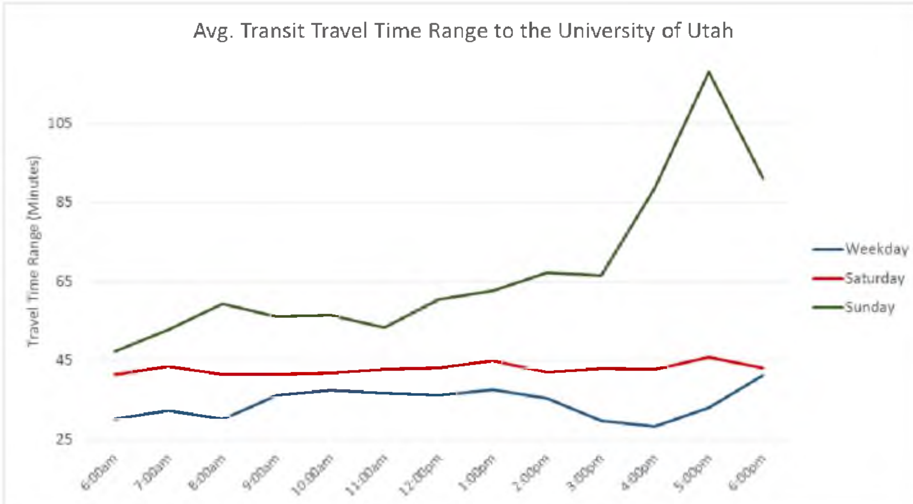


Figure 34: University of Utah travel time range across time.

Table 18: High/low travel time ranges for each day to University of Utah.

	Low Range Peaks	*High Range Peaks*
Weekday	3–4pm	10am
Saturday	2pm; 4pm	11am
Sunday	9am; 11am	8am; 12–2pm

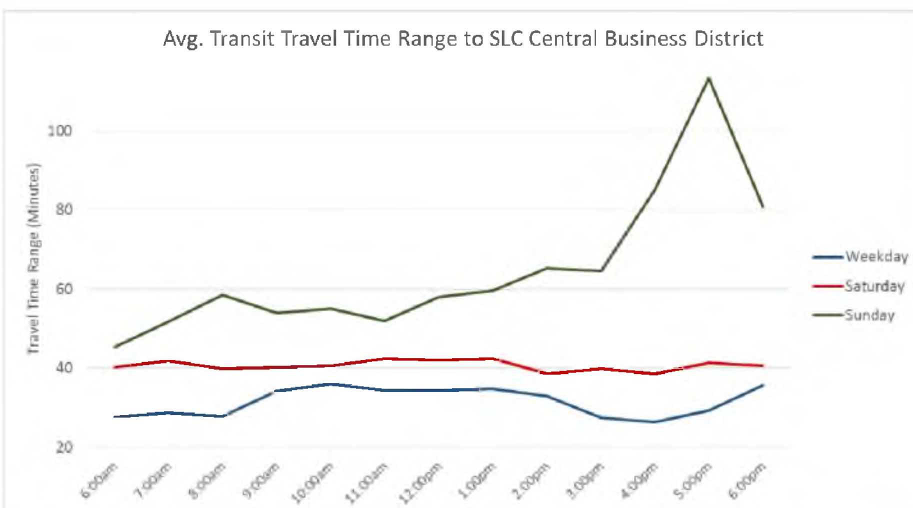


Figure 35: SLC Central Business District travel time range across time.

Table 19: High/low travel time ranges for each day to SLC Central Business District.

	Low Range Peaks	*High Range Peaks*
Weekday	8am; 4pm	10am; 2pm
Saturday	4pm	11am; 1pm
Sunday	6am; 11am	5pm

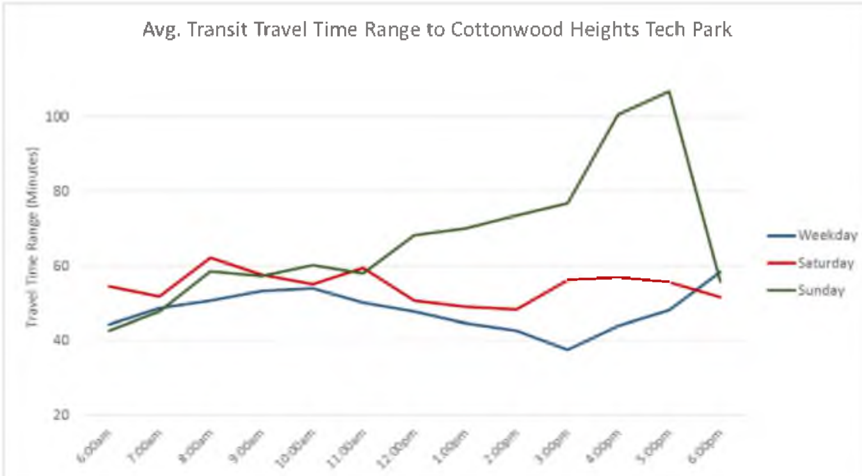


Figure 36: Cottonwood Heights Tech Park travel time range across time.

Table 20: High/low travel time ranges for each day to Cottonwood Heights Tech Park.

	Low Range Peaks	*High Range Peaks*
Weekday	3pm	10am
Saturday	2pm	8am
Sunday	6am	5pm

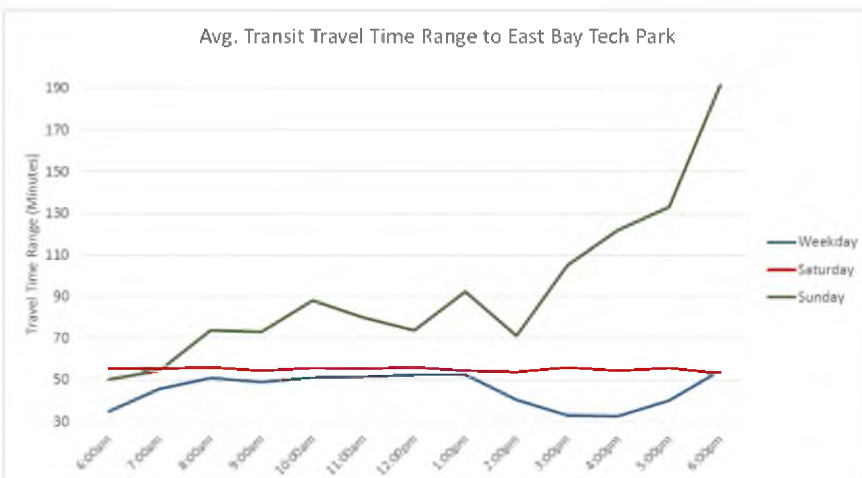


Figure 37: East Bay Tech Park travel time range across time.

Table 21: High/low travel time ranges for each day to East Bay Tech Park.

	Low Range Peaks	*High Range Peaks*
Weekday	3–4pm	1pm
Saturday	4pm	7am
Sunday	6am; 2pm	1pm; 5pm

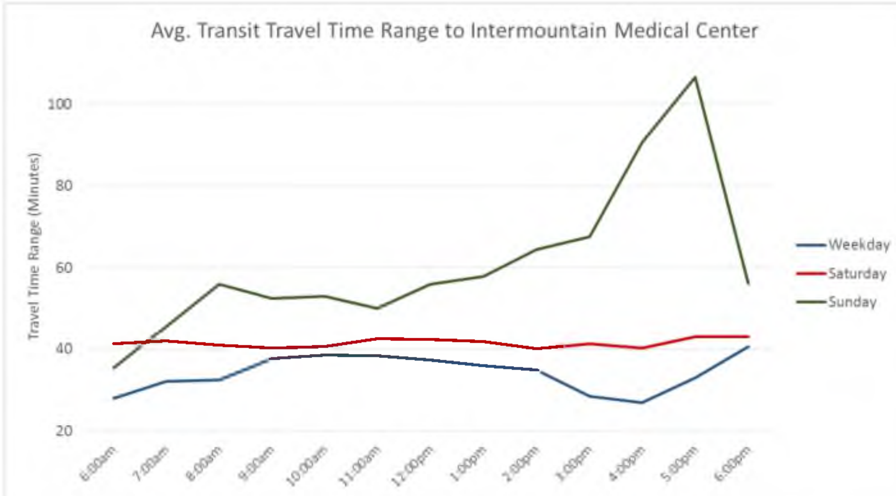


Figure 38: Intermountain Medical Center travel time range across time.

Table 22: High/low travel time ranges for each day to Intermountain Medical Center.

	Low Range Peaks	***High Range Peaks***
Weekday	4pm	10am
Saturday	9am; 2pm; 4pm	11am
Sunday	6am; 11am	2pm; 5pm

Saturday (3pm and 2pm respectively). For the weekday and Saturday, the higher ranges also tended to occur earlier in the morning, around 8–10am. Overall, these results indicate that the low ranges of travel times and, therefore, more consistent service occurred mostly in the morning around 6am and in the late afternoon around 4pm. Also, the higher ranges of travel times and therefore more inconsistent service occurred late morning or early afternoon, particular between the hours of 11am–1pm.

4.2.2 Specific Destinations Travel Speed Analysis

While the travel times to destinations were of importance, the geographic locations of the destinations and the layout of the infrastructure could result in favorable travel times for those locations close together, but in actuality the level of service might not have been better or it may have even been worse than locations farther apart.

Therefore, looking at travel speeds allowed us to instead control for the effect of distance when investigating travel times and more appropriately determine which areas were being provided better service (even if the travel times were longer).

Examining the maps of travel speed helped to show why exploring the travel speeds versus travel times was an important but often forgotten measure of accessibility. While the travel time maps depicted the spatial patterns of travel time, which were related to distance (and especially vertical distance having lower travel times), these travel speed maps and tables for the University of Utah (Figure 39 and Table 23), South Towne Shopping Center (Figure 40 and Table 24), Intermountain Medical Center (Figure 41 and Table 25), SLC Central Business District (Figure 42 and Table 26), the Salt Lake International Airport (Figure 43 and Table 27), and the Cottonwood Heights Technology Park (Figure 44 and Table 28) show that travel time did not give the most accurate view of the quality of service of the network. For example, while the northern and southern ends of the study area tended to have extremely high travel times due to their distance from the specific destinations, the speed maps (Figures 39–44) show that these areas were actually provided fairly good service overall due to the presence of FrontRunner, which is the fastest mode in the network.

As with the travel times, it was also seen that the travel speeds varied throughout the day. A majority of the destinations, such as the University of Utah (Figure 39), the Salt Lake City CBD (Figure 42), the airport (Figure 43), and the Cottonwood Heights Technology Park (Figure 44) all showed similar patterns. For a weekday, the higher travel speeds tended to be during early morning around 6am and also in the evening around 3 or 4pm.

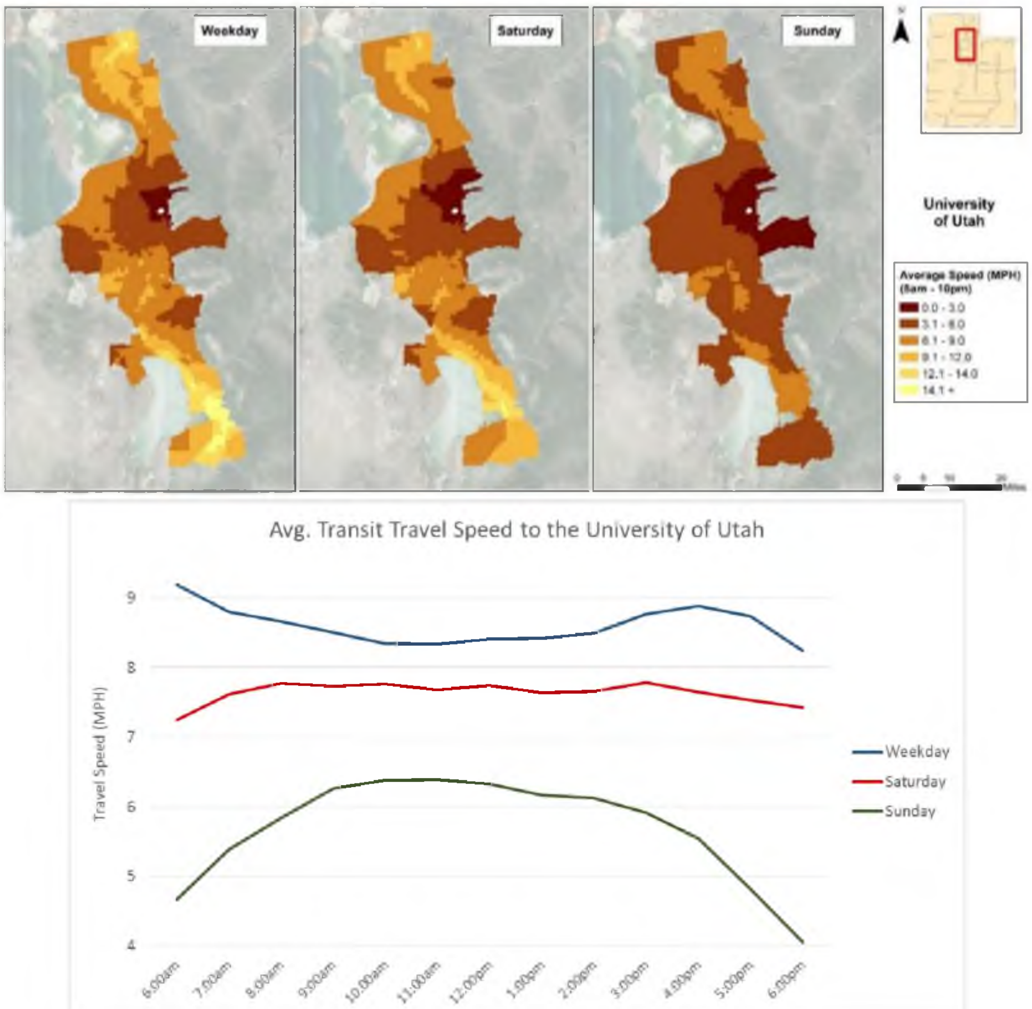
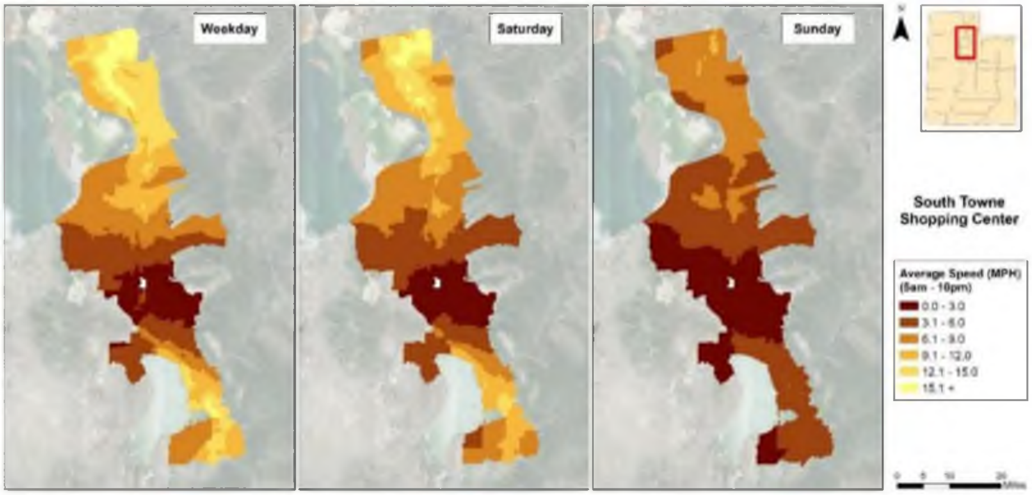


Figure 39: University of Utah travel speed across space (top) and time (btm).

Table 23: High/low travel speeds for each day for University of Utah.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	10am–11am	6am; 4pm
Saturday	6am; 11am; 1pm	8am; 12pm; 3pm
Sunday	6am; 6pm	10–11am



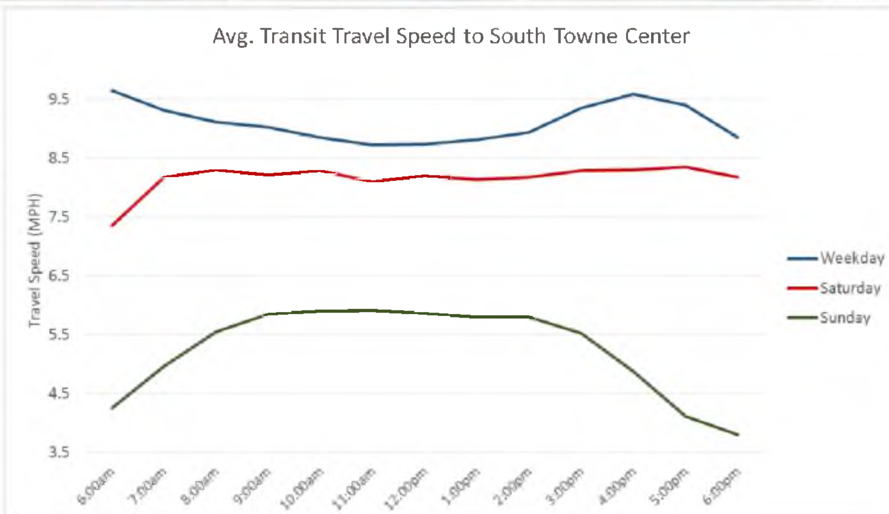


Figure 40: South Towne Center travel speed across space (top) and time (btm).

Table 24: High/low travel speeds for each day for South Towne Center.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	11am–12pm	6am; 4pm
Saturday	6am; 11am	8am; 10am; 5pm
Sunday	6am; 6pm	9–10am

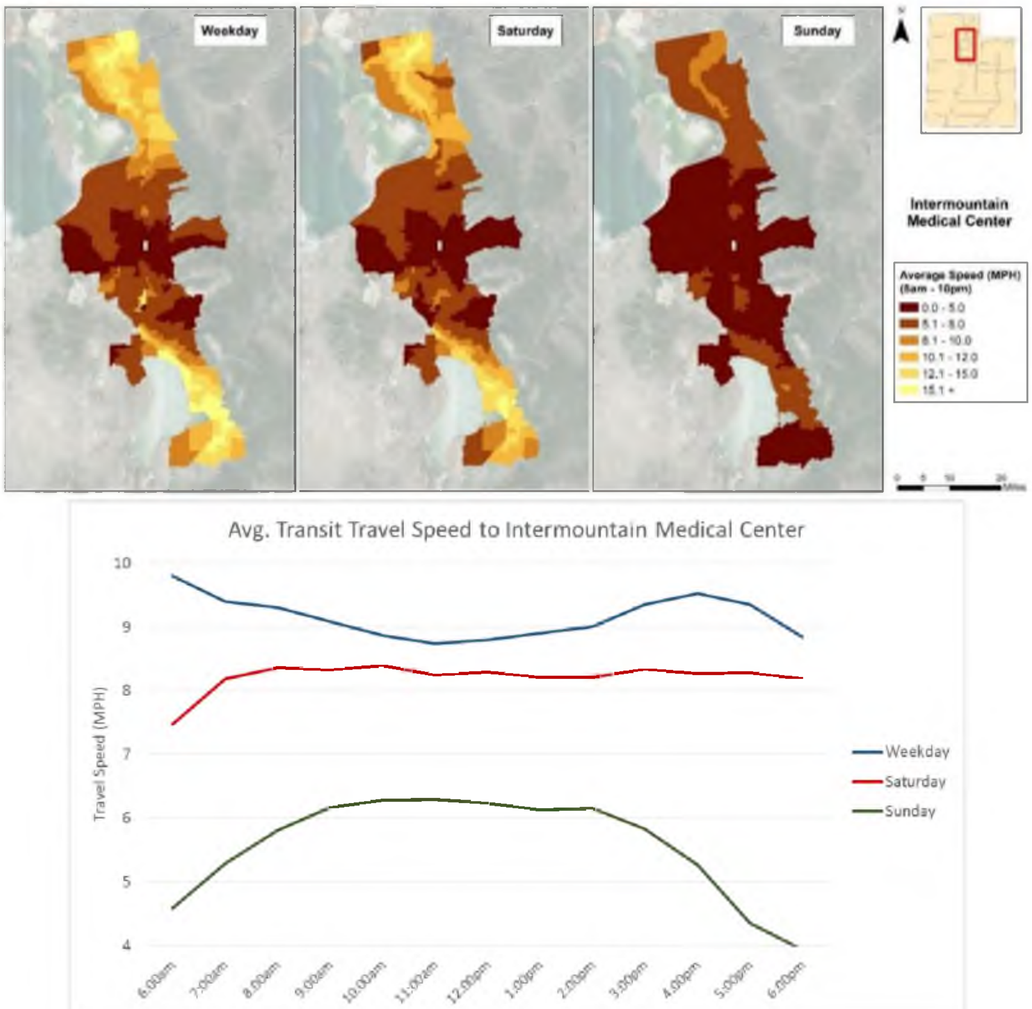


Figure 41: Intermountain Medical Center travel speed across space (top) and time (btm).

Table 25: High/low travel speeds for each day for Intermountain Medical Center.

	Low Travel Speed Peaks	***High Travel Speed Peaks***
Weekday	11am	6am; 8am; 4pm
Saturday	6am; 11am; 2pm	10am; 3pm
Sunday	6am; 6pm	10–11am

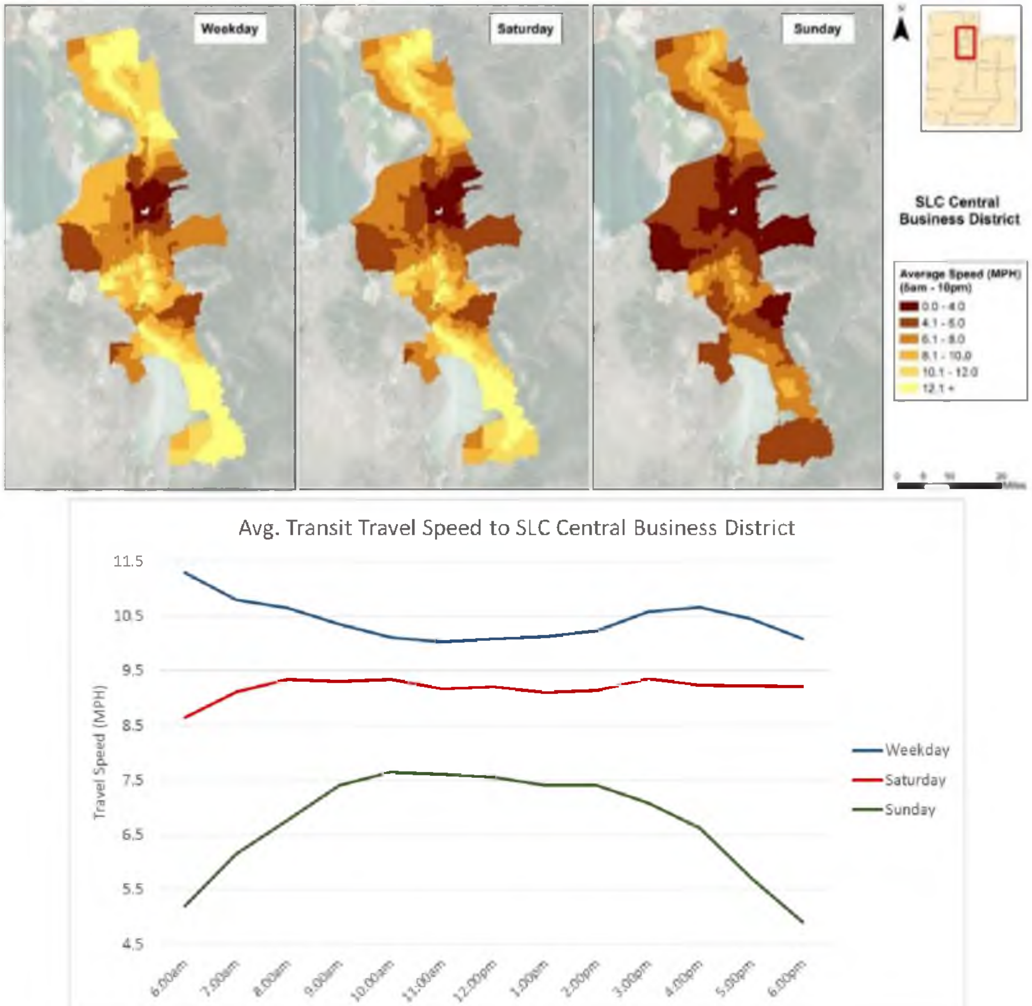


Figure 42: SLC Central Business District travel speed across space (top) and time (btm).

Table 26: High/low travel speeds for each day for SLC Central Business District

	Low Travel Speed Peaks	***High Travel Speed Peaks***
Weekday	10am–12pm	6am; 4pm
Saturday	6am; 11am; 2pm	8am; 10am; 3pm
Sunday	6am; 6pm	10am

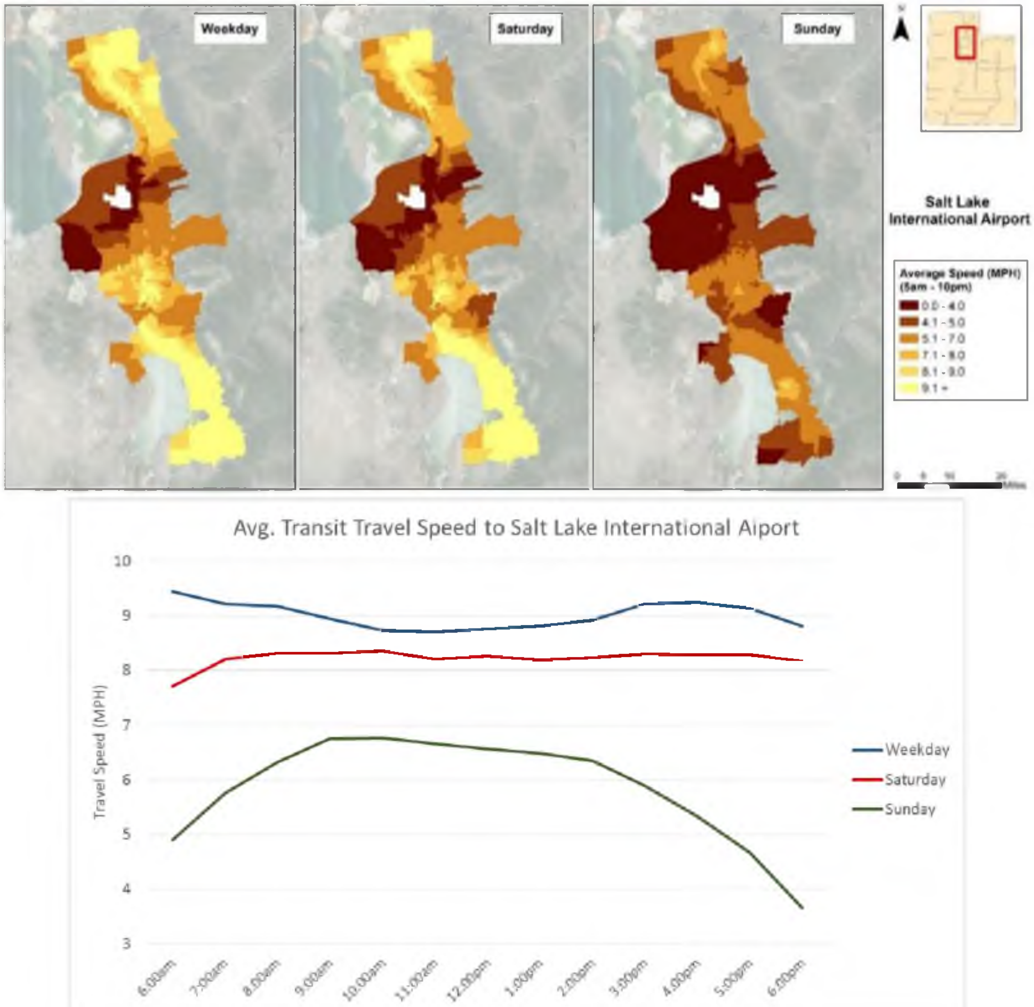


Figure 43: Salt Lake City Intl' Airport travel speed across space (top) and time (btm).

Table 27: High/low travel speeds for each day for Salt Lake City Intl' Airport.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	11am–12pm	6am; 8am; 3pm
Saturday	6am; 11am	10am
Sunday	6am; 6pm	9am

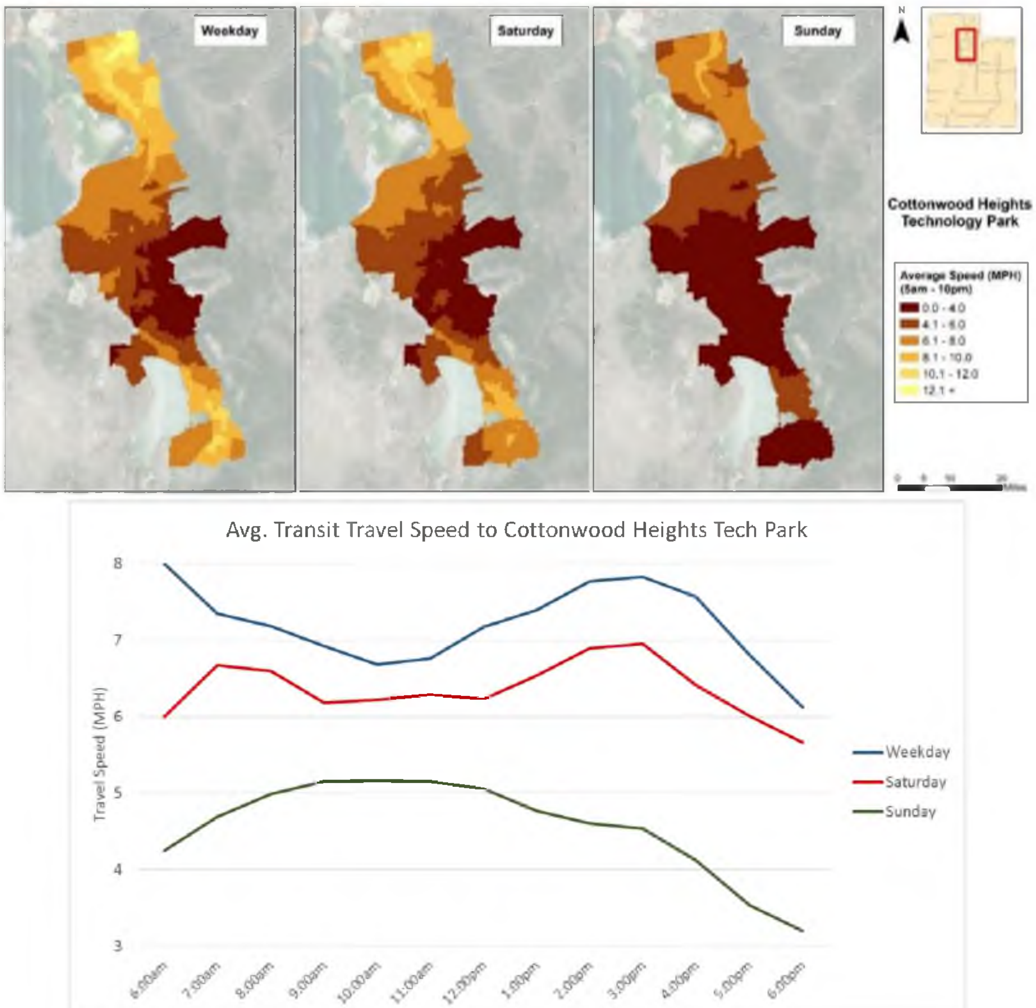


Figure 44: Cottonwood Heights Tech Park travel speed across space (top) and time (btm).

Table 28: High/low travel speeds for each day for Cottonwood Heights Tech Park.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	10am–11am	6am; 2–3pm
Saturday	6am; 9am; 12pm	7am; 3pm
Sunday	6am; 6pm	9am

By contrast, the lower travel speeds tended to be during the middle of the day, around 11am or 12pm. A slightly different trend was noticed on Saturday, with the higher travel speeds being during the late morning, around 10am, followed by the lower travel speeds around 11am or 12pm. Lastly, Sunday depicted that higher travel speeds tended to also be around 10 or 11am, with the lower travel speeds being at the very beginning of the day, around 6am, and at the end of the day, around 6pm.

The results of this section help to indicate that it is clear that performing a public transit accessibility analysis only during rush-hour in the morning or evening would miss the full picture of the transit network since as the network is designed at these hours the travel times tend to be lower, the travel speeds tend to be higher, and the travel range/fluctuation tends to be lower and therefore, the service is more consistent. These off-hours that are often ignored however are when the travel times are higher, travel speeds are lower, and the network experiences the most fluctuations in travel time and less consistent service.

4.2.3 Specific OD Travel Time Analysis

Once it was examined how the travel times from all of the origins to a particular destination fluctuated throughout the day, it was important to explore how the travel times fluctuated throughout the day from a particular origin to a particular destination. While examining how travel times fluctuated from all origins to a particular destination was of interest for that particular destination, most individuals mostly travel between certain origins and destinations, and determining how the travel times and travel speeds varied during the day for those specific trips was more relevant to the rider's experience. Five specific OD pairs were selected to be studied based on these locations being large activity centers in the region. These OD pairs included the SLC Central Business District to the Intermountain Medical Center (Figure 45 and Table 29 of travel times, and Figure 46 and Table 30 of travel time ranges), the University of Utah to the Intermountain Medical Center (Figure 47 and Table 31 of travel times, and Figure 48 and Table 32 of travel time ranges), the Salt Lake International Airport to the University of Utah (Figure 49 and Table 33 of travel times, and Figure 50 and Table 34 of travel time ranges), the South Towne Center to the Cottonwood Heights Technology Park (Figure 51 and Table 35 of travel times, and Figure 52 and Table 36 of travel time ranges), and lastly, the Salt Lake International Airport to Hill Air Force Base (Figure 53 and Table 37 of travel times, and Figure 54 and Table 38 of travel time ranges).

Connectivity between each OD pair was illustrated using three figures and two summary tables. The first figure for each OD pair examined the minute-by-minute fluctuations in travel times on a weekday. These charts allowed for a more in-depth analysis into how from 1 minute to another the travel time for the OD pair might jump almost 20–30 minutes due to missing the bus or train. They also helped to highlight when the network fluctuated throughout the day, and if these fluctuations are large from 1 minute to another or over different hours. The second figure, smoothed average charts, showed the overall trends much more easily, such as when the average travel times became higher or lower, but you could not see how much fluctuation was occurring. Next, the travel time range charts, however, helped to compensate for this by highlighting the range (maximum travel time – minimum travel time) for each hour.

As can be seen by examining Figure 45 and Table 29, Figure 46 and Table 30, Figure 47 and Table 31, and Figure 48 and Table 32, fluctuations were present during the

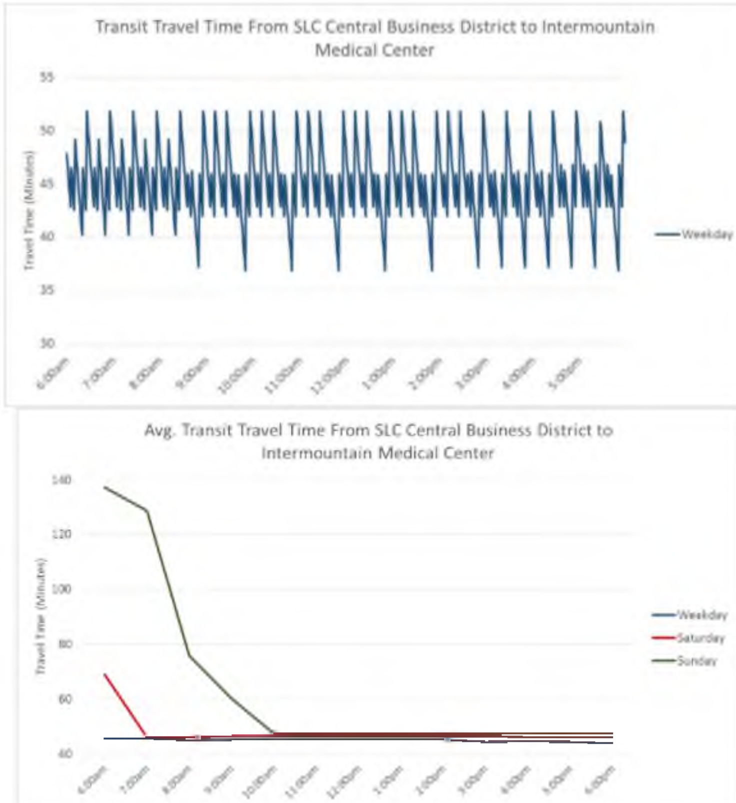


Figure 45: SLC Central Business District to Intermountain Medical Center minute-by-minute travel times (top) and avg. travel times (btm).

Table 29: High/low travel times for each day for the Figure 45 OD pair.

	Low Travel Time Peaks	***High Travel Time Peaks***
Weekday	6pm	6am
Saturday	7am	10am
Sunday	10am	6pm

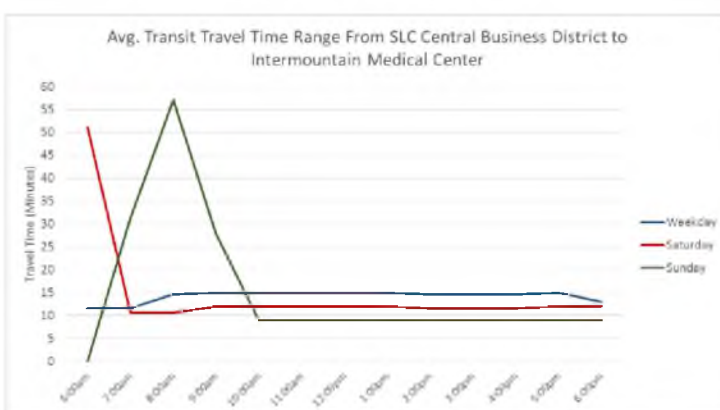
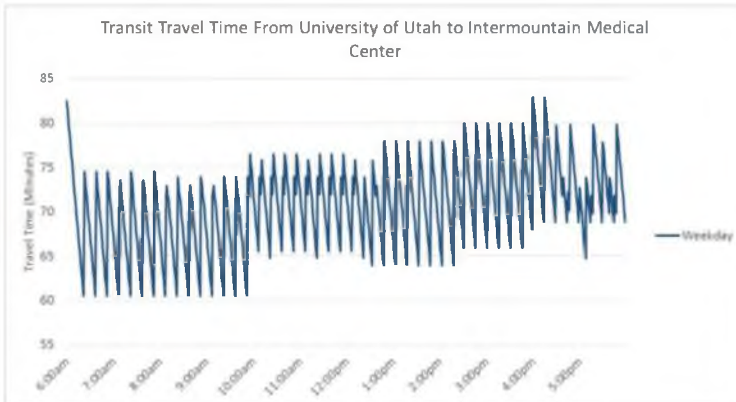


Figure 46: SLC Central Business District to Intermountain Medical Center avg. travel time range.

Table 30: High/low travel time ranges for each day for the Figure 46 OD pair.

	Low Range Peaks	*High Range Peaks*
Weekday	7am	8am–1pm
Saturday	7–8am	9am–1pm
Sunday	10am–5pm	9am



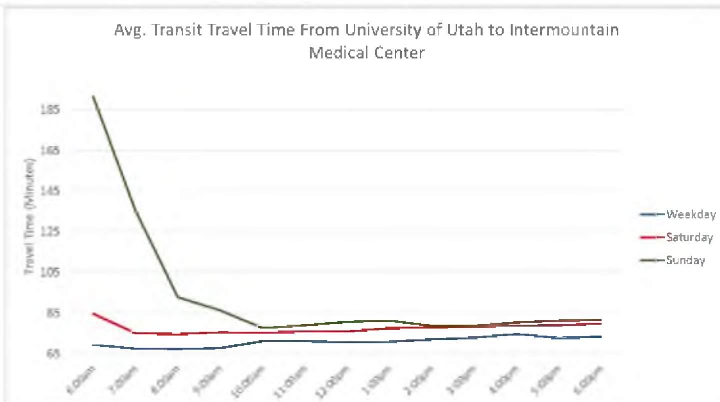


Figure 47: University of Utah to Intermountain Medical Center minute-by-minute travel times (top) and avg. travel times (btm).

Table 31: High/low travel times for each day for the Figure 47 OD pair.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	8–9am	10am; 4pm
Saturday	7am	6am; 6pm
Sunday	2–3pm	12–1pm

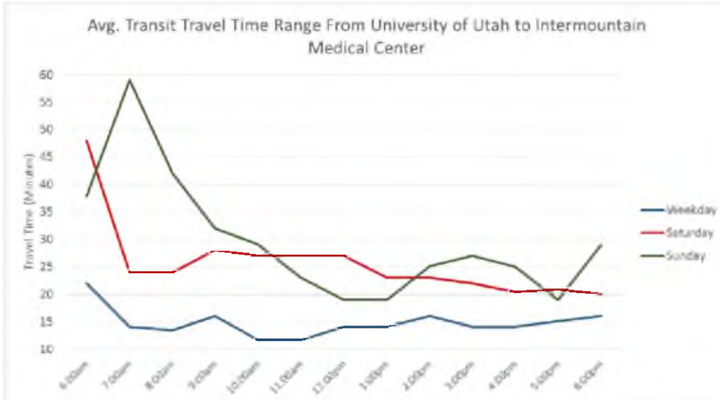


Figure 48: University of Utah to Intermountain Medical Center avg. travel time ranges.

Table 32: High/low travel time ranges for each day for the Figure 48 OD pair.

	Low Range Peaks	***High Range Peaks***
Weekday	10–11am	9am; 2pm
Saturday	4–5pm	9am; 12pm
Sunday	12–1pm	10am; 3pm

hours of 6am and 6pm. However, there were differences between the magnitude of these fluctuations, with some of the OD pairs, such as the Salt Lake City Central Business District to the Intermountain Medical Center (Figures 45 and 46) and from the University of Utah to the Intermountain Medical Center (Figures 47 and 48) having fairly small fluctuations of only about 5–15 minutes being noticed throughout the day.

However, some OD pairs (Figure 49 and Table 33, Figure 50 and Table 34, Figure 51 and Table 35, Figure 52 and Table 36, Figure 53 and Table 37, and Figure 54 and Table 38) displayed much larger fluctuations and therefore appeared farther apart on the graph. In particular, two of the three OD pairs in which the origin was the Salt Lake International Airport (airport to University of Utah in Figures 49 and 50, and the airport to Hill Air Force Base in Figures 53 and 54), as well as from South Towne Center to Cottonwood Heights Technology Park (Figures 51 and 52), highlighted where major fluctuations of around 30–40 minutes occurred throughout the day, which was much

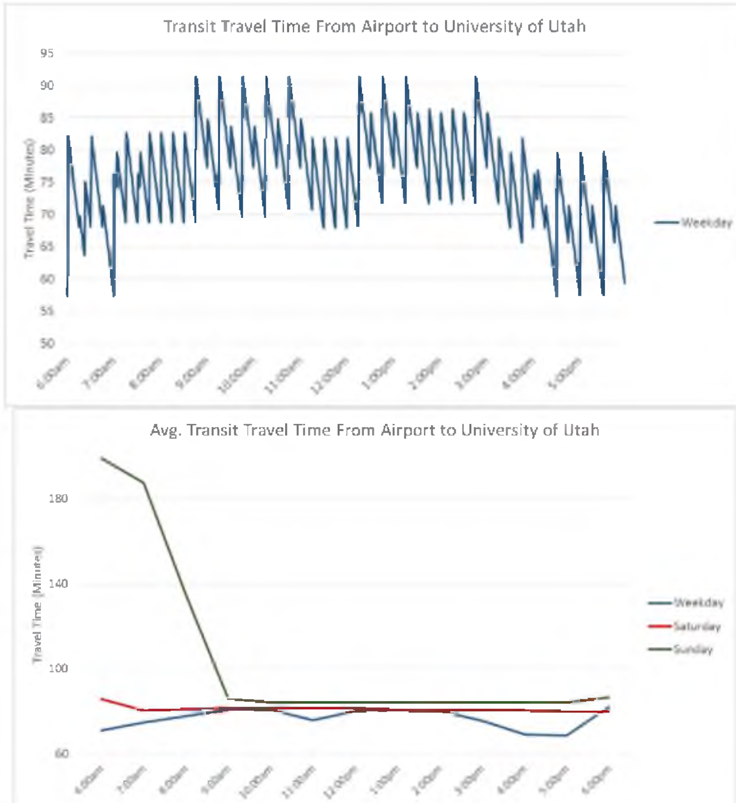


Figure 49: Salt Lake Intl' Airport to University of Utah minute-by-minute travel times (top) and avg. travel times (btm).

Table 33: High/low travel times for each day for the Figure 49 OD pair.

	Low Travel Time Peaks	***High Travel Time Peaks***
Weekday	6am; 4–5pm	10am
Saturday	7am	6am
Sunday	10am	9am

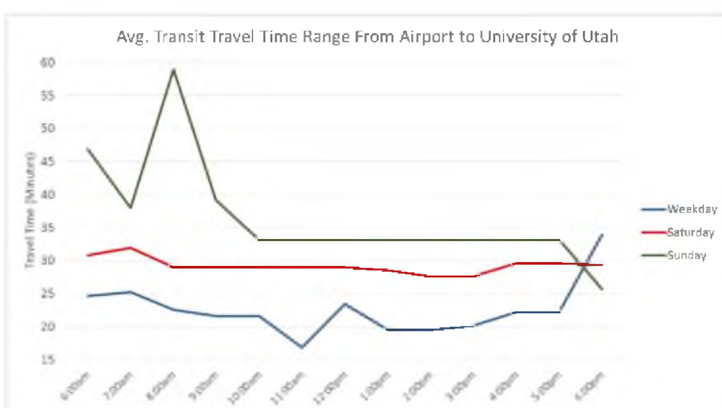


Figure 50: Salt Lake Intl' Airport to University of Utah avg. travel time ranges.

Table 34: High/low travel time ranges for each day for the Figure 50 OD pair.

	Low Range Peaks	*High Range Peaks*
Weekday	11am	7am; 12pm
Saturday	2–3pm	7am; 4pm
Sunday	10am–5pm	9am

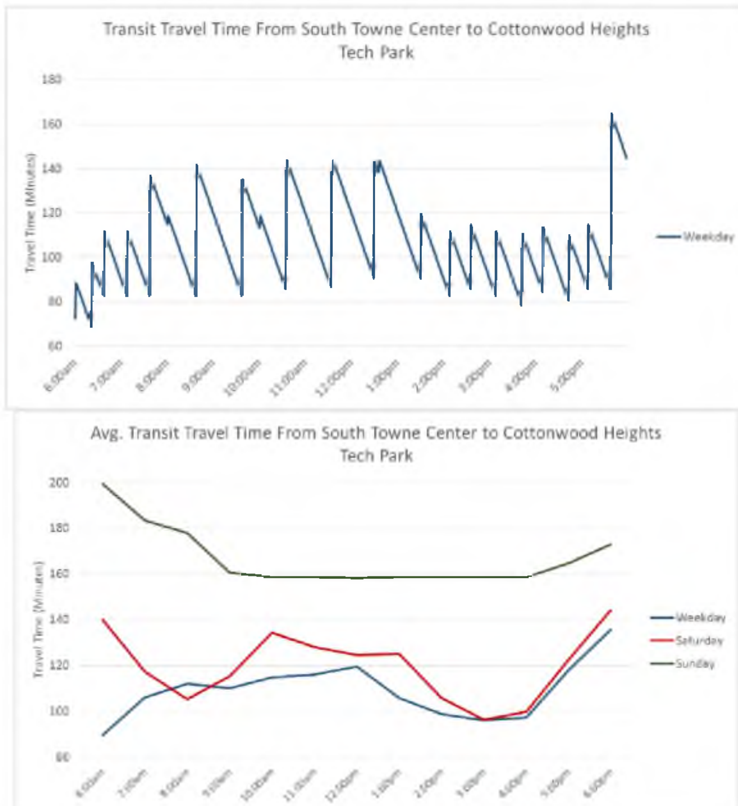


Figure 51: South Towne Center to Cottonwood Heights Tech Park minute-by-minute travel times (top) and avg. travel times (btm).

Table 35: High/low travel times for each day for the Figure 51 OD pair.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	3–4pm	12pm
Saturday	8am; 3–4pm	10am; 1pm
Sunday	11am–4pm	9am; 6pm

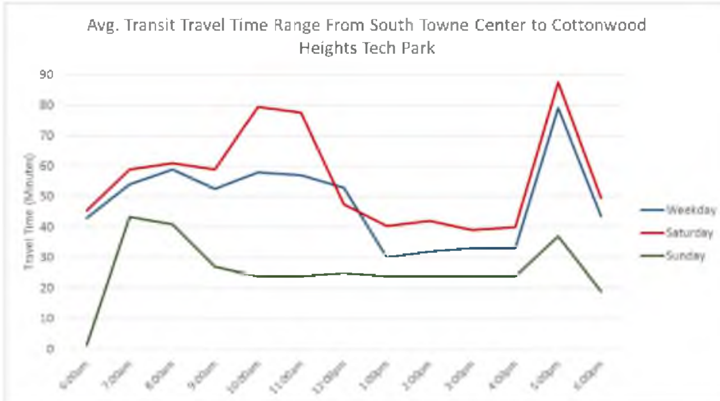


Figure 52: South Towne Center to Cottonwood Heights Tech Park avg. travel time ranges.

Table 36: High/low travel time ranges for each day for the Figure 52 OD pair.

	Low Range Peaks	***High Range Peaks***
Weekday	1–2pm	8am; 10am; 5pm
Saturday	3–4pm	10–11am; 5pm
Sunday	2–4pm	12pm

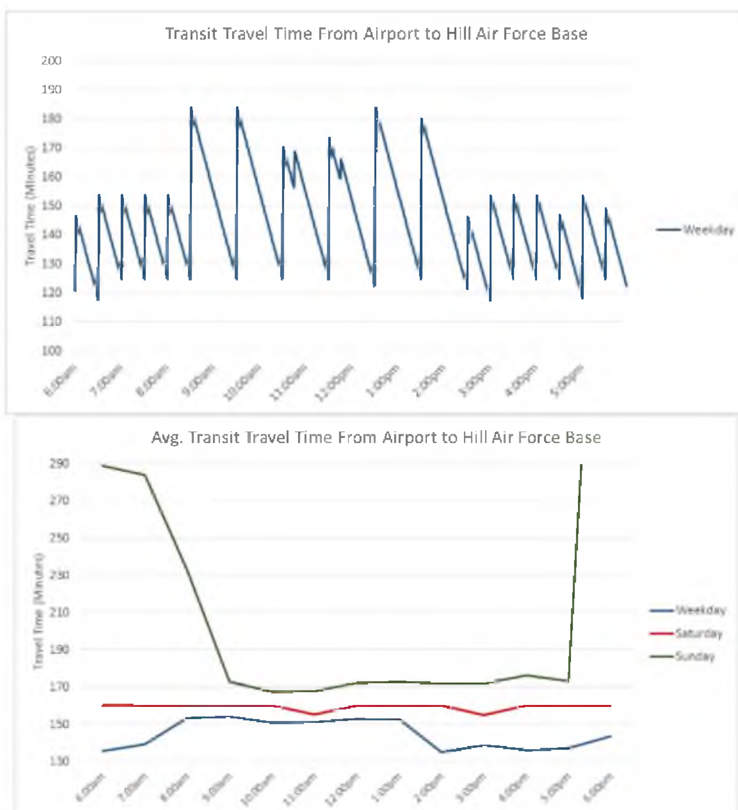


Figure 53: Salt Lake Intl' Airport to Hill Air Force Base minute-by-minute travel times (top) and avg. travel times (btm).

Table 37: High/low travel times for each day for the Figure 53 OD pair.

	Low Travel Time Peaks	*High Travel Time Peaks*
Weekday	6am; 2pm	8am; 1pm
Saturday	11am; 3pm	10am; 4pm
Sunday	10am–11am	4pm

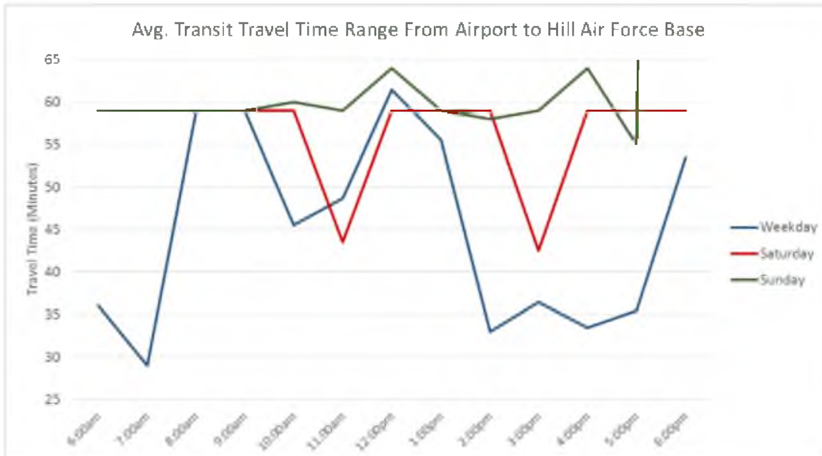


Figure 54: Salt Lake Intl' Airport to Hill Air Force Base avg. travel time ranges.

Table 38: High/low travel time ranges for each day for the Figure 54 OD pair.

	Low Range Peaks	*High Range Peaks*
Weekday	7am; 2pm; 4pm	8–9am; 12pm
Saturday	11am; 3pm	9–10am; 12–2pm
Sunday	2pm; 5pm	12pm; 4pm

larger than the 5–15 seen in the other OD pairs (Figures 45–48).

The averaged travel time graphs could be used to summarize the minute-by-minute graphs and to identify generalized shifts in travel times throughout the day. First, when examining the start and end times of service, as well as the times during the day when the travel times were the highest and when they were the lowest, for most of the OD pairs similar patterns emerged. Overall, transit service tended to begin around 5–6am in the morning on a weekday and started only slightly later on a Saturday, normally around 6 or 7am. Lastly, Sunday service started even later in the morning at around 9am. For service end times, most of the OD pairs noticed abrupt increases in travel times around 8 or 9pm. Sunday noticed the increase much earlier, at around 5 or 6pm. The times of the lowest and highest travel times were also similar. For most of the OD pairs on the weekday and Saturday, the lower travel times tended to be around 6 to 7am, with another dip in travel times in the evening, around 4 or 5pm. Sunday normally witnessed the lowest travel times around midmorning at 10am. For the higher travel times, these tended to be around 11am–12pm, and again around 2–3pm on weekdays and Saturdays. For Sundays, the higher travel times tended to be midmorning, around 9am.

Similar patterns were seen when examining how the ranges in travel time fluctuated throughout the day. For most of the OD pairs, the times for the weekday when the travel time ranges are lower and therefore depict less fluctuation were around 7 or 8am. There was also less fluctuation in the late morning, around 11am. During the weekday, the highest ranges tended to be just after the lower ranges, appearing around 8 or 9am in the morning and around 12 or 1pm in the afternoon. For Saturdays, the lower ranges also occurred in the morning around 7–8am, with another period being around 2 or 3pm. The higher travel time ranges tended to appear right before and after the afternoon period, with the higher travel time ranges being around 12pm and again around 4pm. Lastly, for Sunday, the lower travel time ranges were later in the morning than the previous days, at around 9am, but also earlier in the afternoon around 2pm. There was variation between the OD pairs about when the higher travel time ranges appear, but most often they occurred between 9am and 12pm. The levels of fluctuations were most likely the result of the transit network infrastructure. Those OD pairs that experience little fluctuation tended to rely solely on TRAX to get from the origin to the destination. However, those OD pairs that experienced quite a bit of fluctuation might rely almost entirely on the bus. From this, it would seem that the TRAX mode provided a more consistent travel time from a specific origin to a specific destination across an entire day. However, an OD pair that relied mostly on bus tended to have a more inconsistent travel time throughout the day.

4.2.4 Specific OD Travel Speed Analysis

As mentioned, geographic distances can result in overexaggerated or underexaggerated travel times. Therefore, looking at travel speeds allowed for a better understanding of level of service being provided.

Compared to most of the other analyses performed where most of the OD pairs exhibited similar patterns across all three of the days, when examining the travel speeds between specific OD pairs, a wide range of differences were noticed, especially in regards to Saturday and Sunday service. First, for the weekday, most of the higher travel speeds were exhibited early in the morning around 6am and again during the late afternoon around 4pm. The main difference being for the University of Utah to the Intermountain Medical Center (Figure 55 and Table 39) when the higher travel speeds were around 8 in the morning and the lower travel speeds were during the late afternoon around 4pm. For some of the OD pairs, the higher travel speeds on Saturday were around 1pm with the lower travel speeds between 9 and 11am. However, differences were noticed for several of the OD pairs. For the Airport to Hill Air Force Base (Figure 56 and Table 40) and for the South Towne Center to the Cottonwood Heights Technology Park (Figure 57 and Table 41), the lower travel speeds tended to be around 11am and 3pm, with the higher travel speeds between these two times. For the University of Utah to the Intermountain Medical Center (Figure 58 and Table 42), a difference is again witnessed,

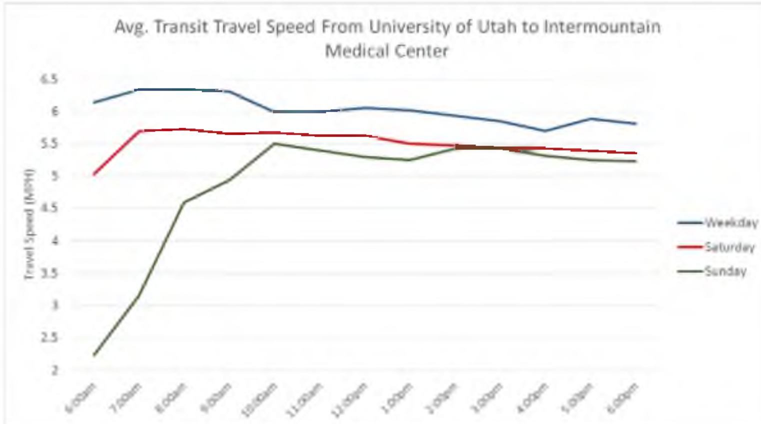


Figure 55: University of Utah to Intermountain Medical Center avg. travel speed.

Table 39: High/low travel speeds for each day for the Figure 55 OD pair.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	4pm	7–9am
Saturday	6pm	7–8am
Sunday	1pm	10am; 2–4pm

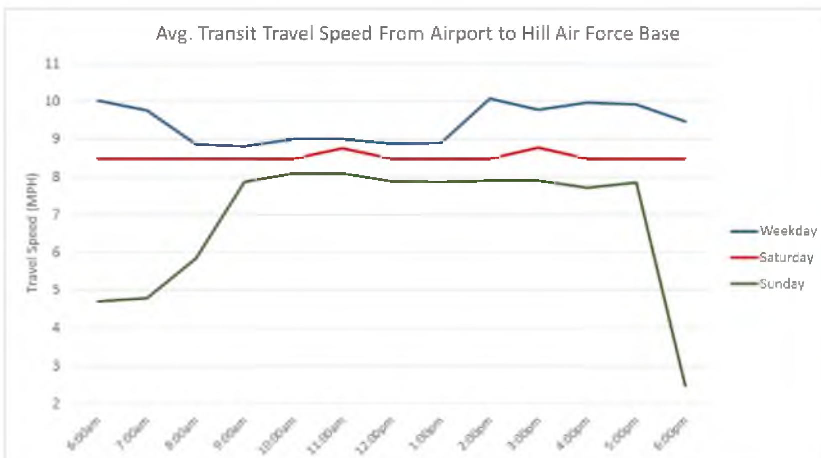


Figure 56: Salt Lake Intl' Airport to Hill Air Force Base avg. travel speed.

Table 40: High/low travel speeds for each day for the Figure 56 OD pair.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	8–9am; 1pm	7am; 2pm
Saturday	12–2pm	11pm; 3pm
Sunday	4pm	10am–11am

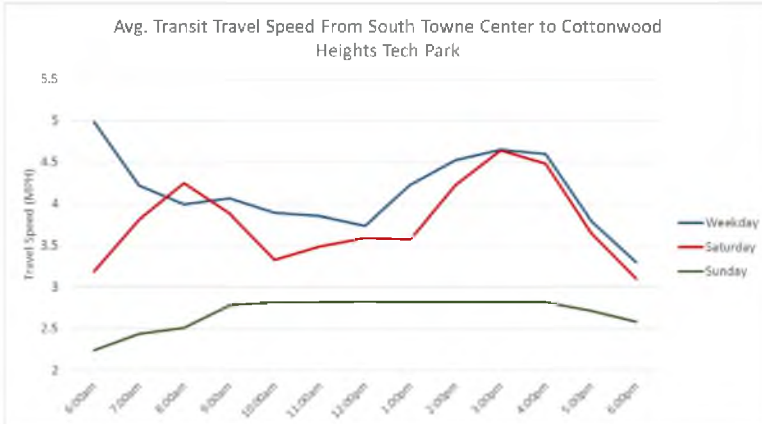


Figure 57: South Towne Center to Cottonwood Heights Tech Park avg. travel speed.

Table 41: High/low travel speeds for each day for the Figure 57 OD pair.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	12pm	6am; 3–4pm
Saturday	10am	8am; 3pm
Sunday	9am	10am–2pm

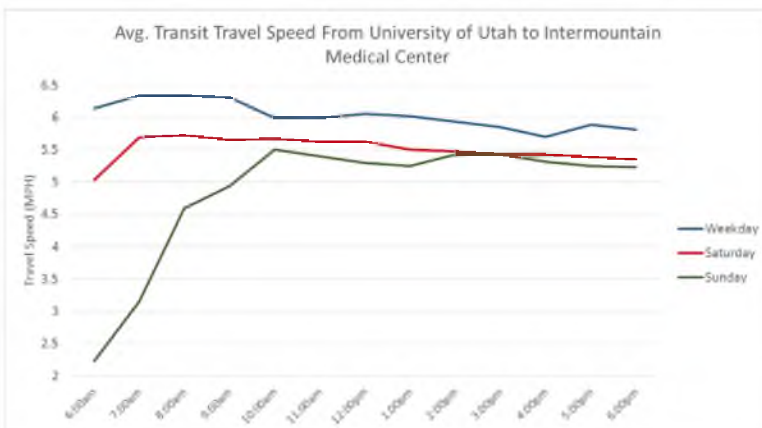


Figure 58: University of Utah to Intermountain Medical Center avg. travel speed.

Table 42: High/low travel speeds for each day for the Figure 58 OD pair.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	4pm	7–9am
Saturday	6pm	7–8am
Sunday	1pm	10am; 2–4pm

with the higher travel speeds being around 7am and the higher travel speeds right before that at 6am. Lastly, for Sunday, most of the OD pairs had higher travel speeds around 10am with the lower travel speeds before that at 9am. However, from the SLC Central Business District to the Intermountain Medical Center (Figure 59 and Table 43) and from the Airport to Hill Air Force Base (Figure 56 and Table 40), the lower travel speeds tended to be later in the afternoon, around 4pm.

Examining travel speed in relation to the specific OD pairs helped to highlight that while travel times from most origins to most destinations might be the best or worst at similar times of the day, travel speeds can fluctuate much more depending on the locations and the primary mode that services them. As the distance figures showed prior, the northern and southern portions of the study area were provided with the fastest travel speeds due to FrontRunner, as well as OD pairs that were north-south, and this could be seen with the higher travel speeds being associated with OD pairs that were oriented north-south, and the lower travel speeds associated with the OD pairs that were east-west.

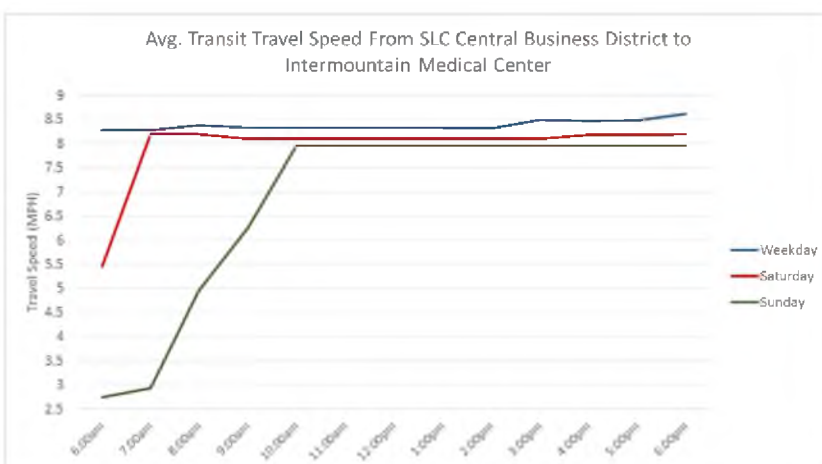


Figure 59: Salt Lake City CBD to Intermountain Medical Center avg. travel speed.

Table 43: High/low travel speeds for each day for the Figure 59 OD pair.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Weekday	9am–2pm	3–4pm
Saturday	9–11am	1pm
Sunday	9am–3pm	4pm

4.2.5 Sociodemographic Accessibility to Destinations (Time)

The last major analysis in this section included examining if differences in travel times to destinations existed between sociodemographic groups. Overall, this involved calculating the weighted average travel time and travel speed for each sociodemographic group from the origins to the destinations. Then, the same type of analysis was performed by exploring the differences from the origins to specific destinations of interest to determine how socially equitable the transit network was for sociodemographic groups to certain destinations. The destinations in this part of the analysis included the Salt Lake International Airport, the University of Utah, the Intermountain Medical Center, the East Bay Technology Park, the SLC Central Business District, and the South Towne Center. As will be seen, it was important to investigate both the weighted travel time and the weighted travel speed. For example, the travel time for a particular sociodemographic group to a destination might have been low compared to others due to physical proximity, but the travel speed indicated whether the transport infrastructure inadvertently favors one social group over another. The sociodemographics groups that were explored are shown in Table 44, as well as the reference factor level that was used for comparison. In addition, Figures 60–65 depict maps showing the spatial distribution of each of the different factor levels in the demographic groups. It was determined that the total number of individuals in a certain factor level was easier to view than percentages (since the percentages were fairly low in many cases).

Table 44: Sociodemographic groups and the reference factor that was analyzed.

Socio-Demographic Group	Reference Factor
Age	18–64
Mode	Auto
Disability	Non-Disabled
Employment	Employed
Hispanic?	Non-Hispanic
Occupation	Health/Service
Education	Higher Ed.
Race	White
Income	$35,000–$75,000

When examining the aggregated weighted travel time average between all locations, it is seen in Figures 60–65 that some variation was present. Figure 66 depicts how each factor level of the different social groups compared to the reference factor level of that social group. A value of 1 indicated that there was no difference in travel times between the specific factor level and the reference factor level. A value above 1 indicated that the specific factor level in the social group tended to have higher travel times than the reference factor level, with a value below 1 indicating the opposite. As Figure 66 indicates, for the whole study area, travel times decreased with age. For household income, those in households that made under $35,000 had lower travel times and those that made over $75,000 tended to have higher travel times. Examining race and ethnicity together showed equal findings, with both those considered Hispanic and those considered non-White having lower travel times than those that are non-Hispanic and White, respectively. Lastly, when examining disability status, it was seen that those considered disabled had lower travel times than those that were not disabled. In total, it was seen that inequality existed between the different factor levels in the demographic groups, but for the most part, the direction of inequality was progressive, with those at risk of social exclusion being able to travel shorter durations to reach destinations.

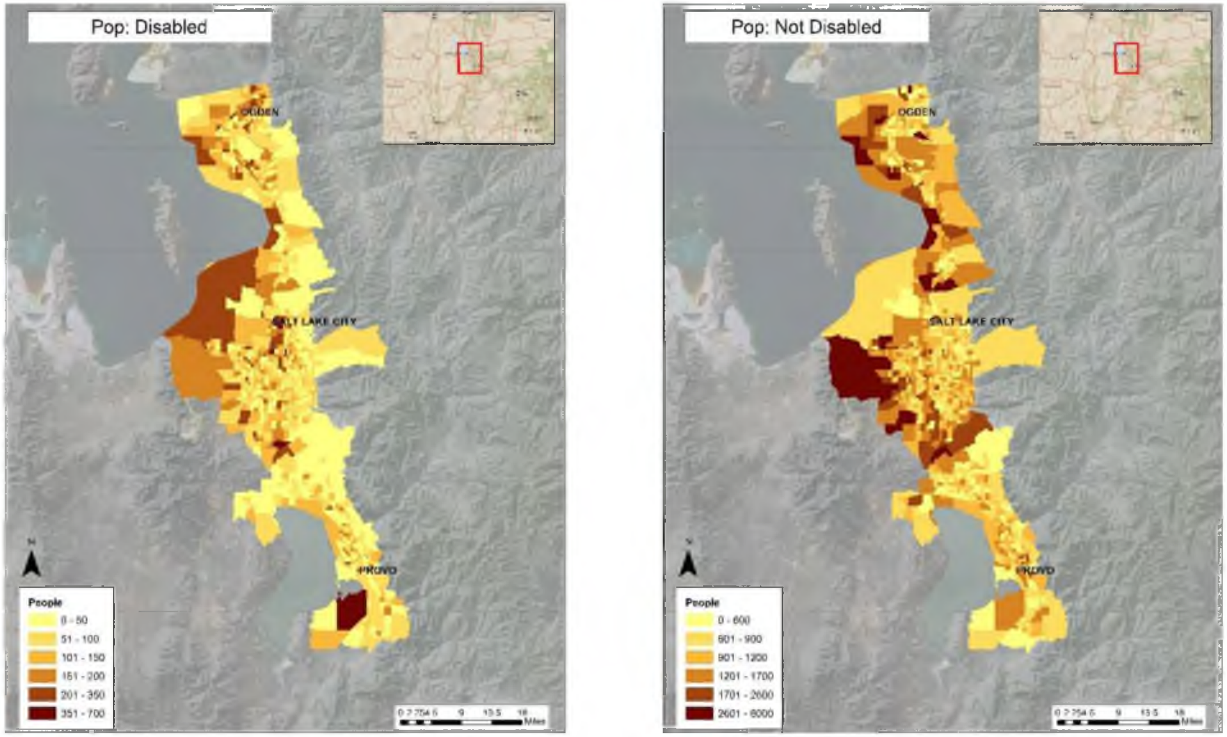


Figure 60: Disabled (left) and non-disabled (right) populations in the study area.

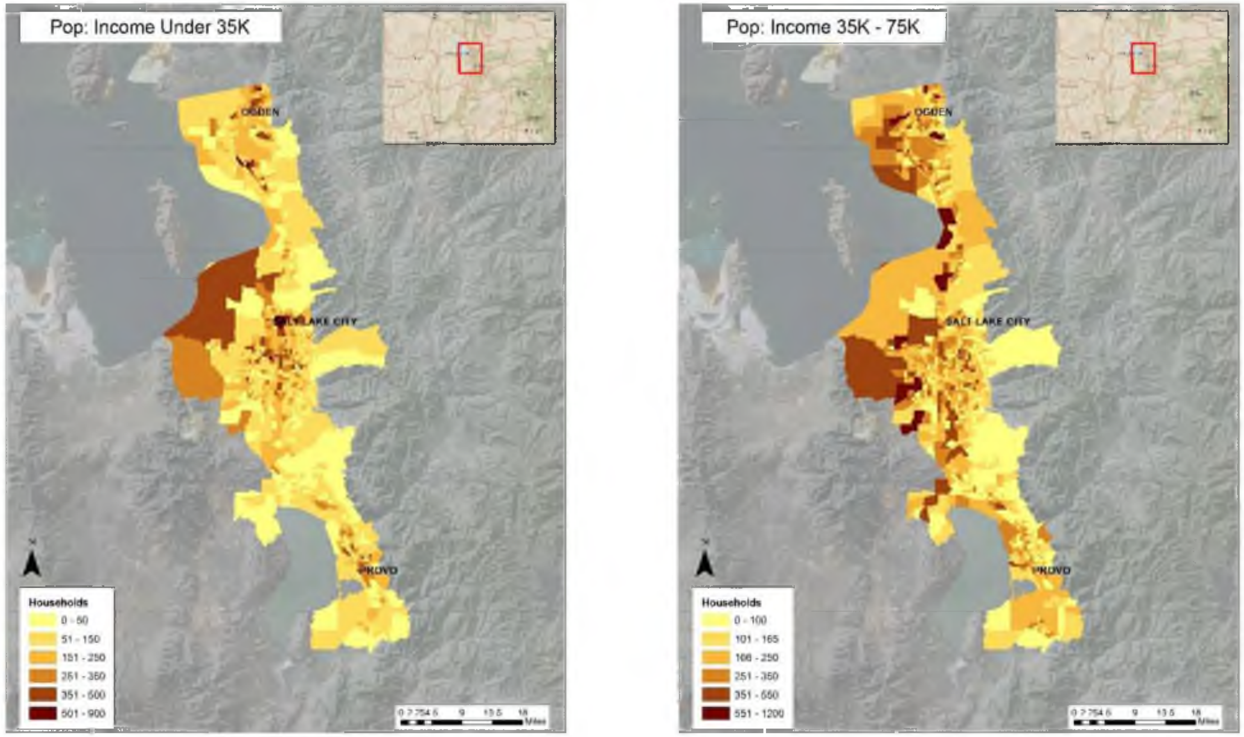


Figure 61: Income <35k (left) and income 35k–75k (right) populations in the study area.

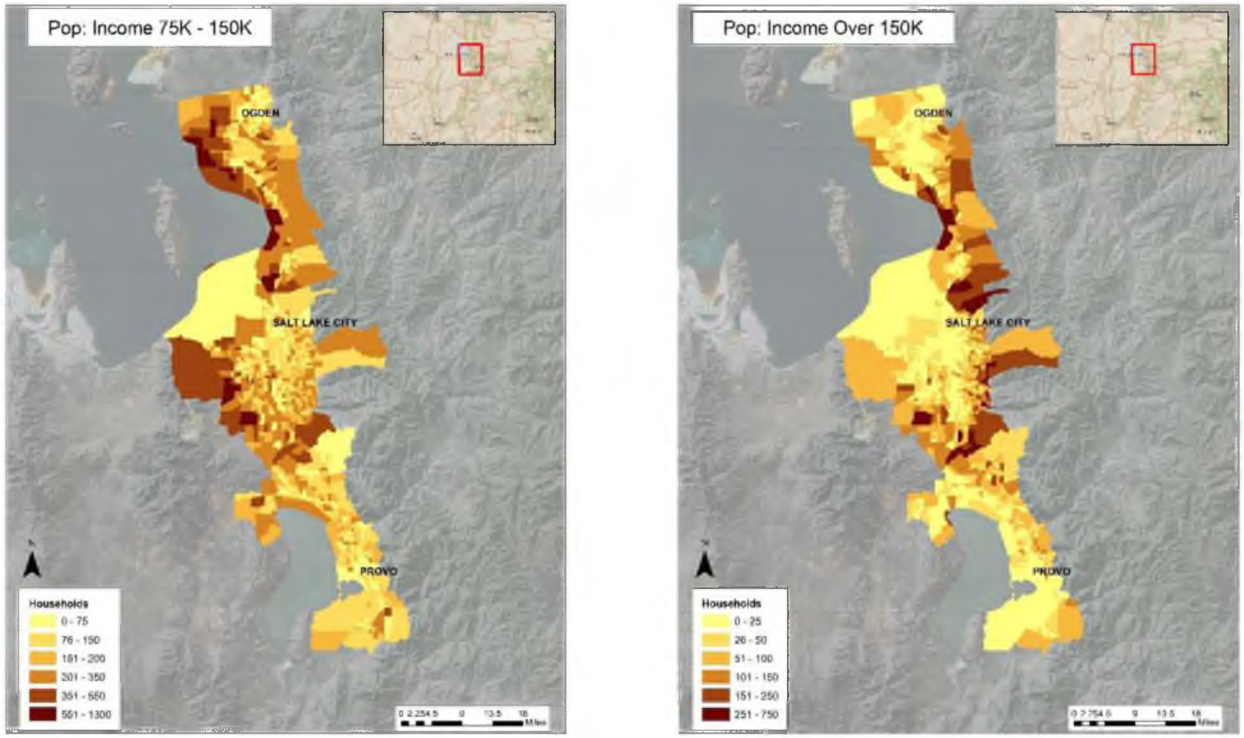


Figure 62: Income 75k–150k (left) and income >150k (right) populations in the study area.

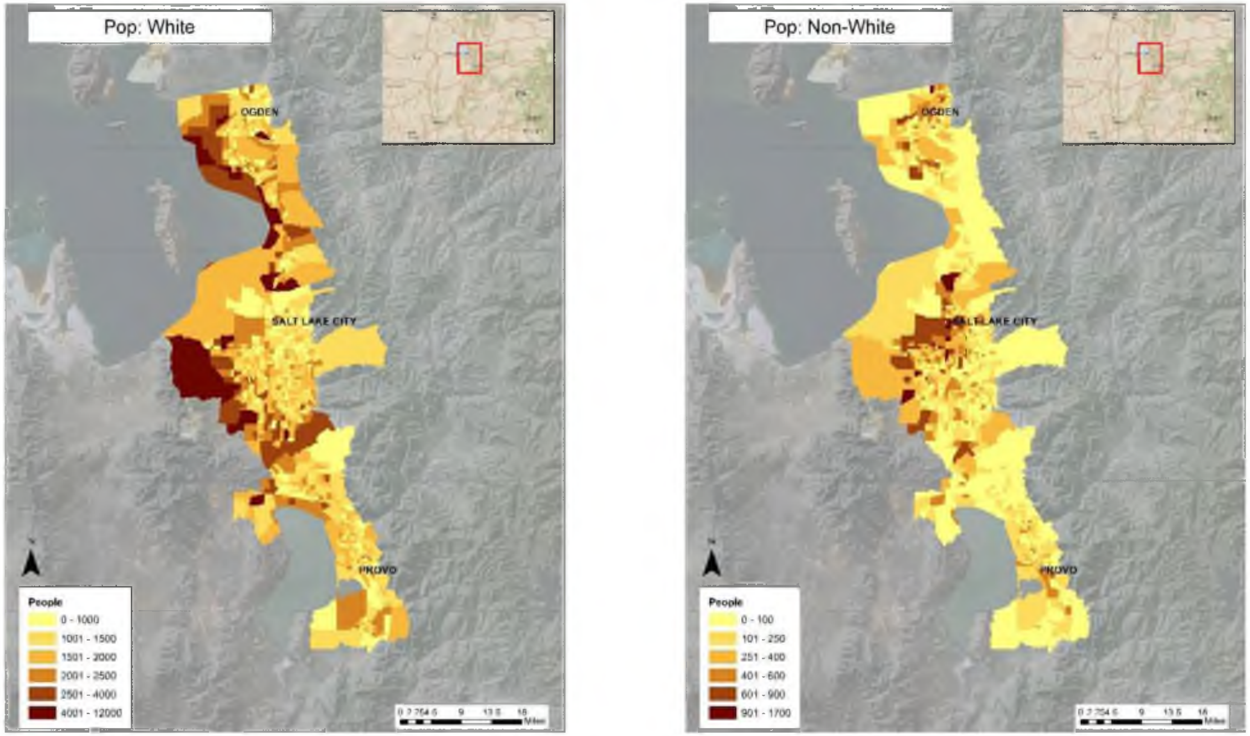


Figure 63: White (left) and non-White (right) populations in the study area.

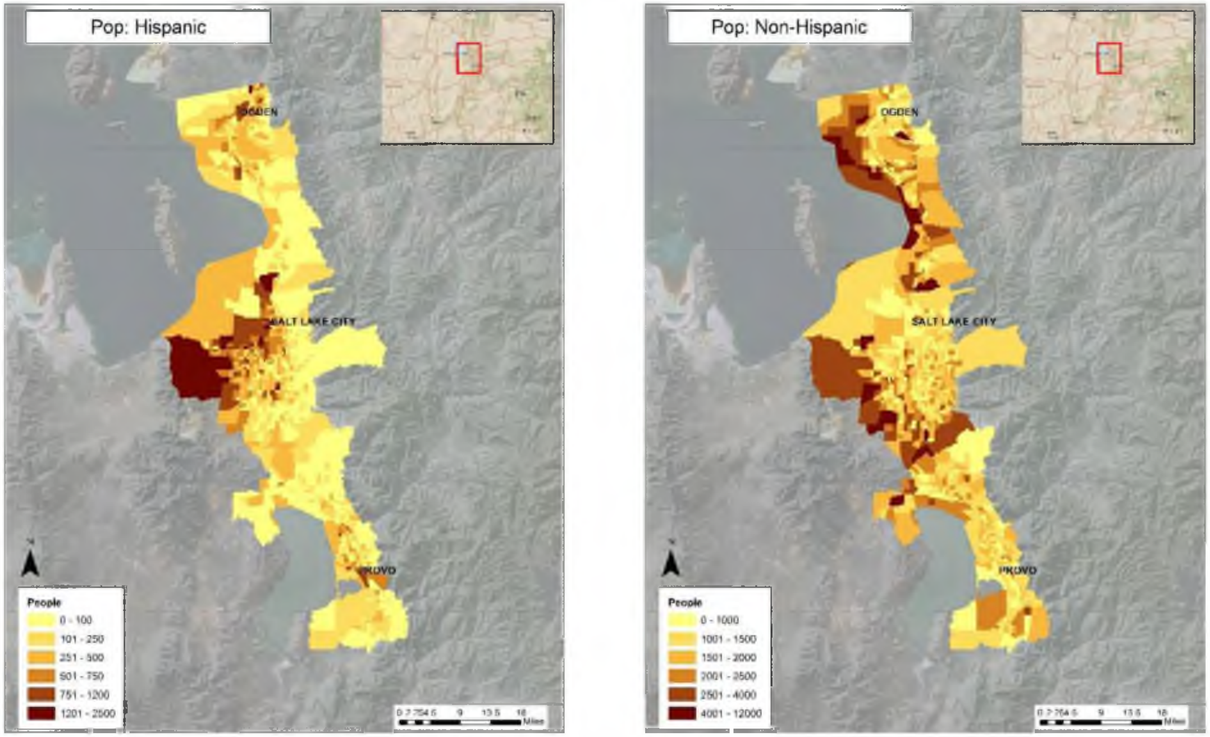


Figure 64: Hispanic (left) and non-Hispanic (right) populations in the study area.

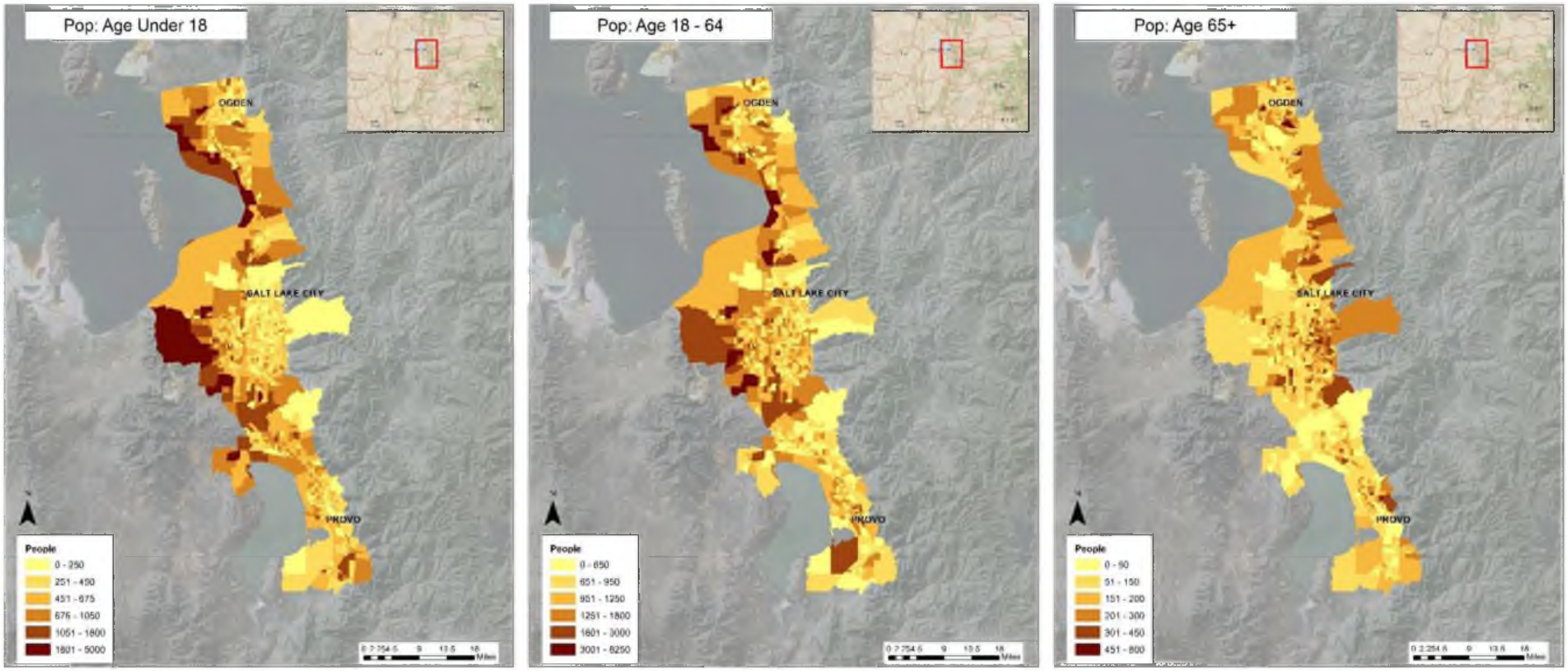


Figure 65: Aged <18 (left), aged 18–64 (middle), and aged >65 (right) populations in the study area.

While these results in Figure 66 highlight how the different factor levels in the sociodemographic groups varied in travel times across the entire study area, it was also important to examine if these same levels in inequality were present to specific destinations. While overall accessibility of a transit network is desirable, having social equality to certain destinations, such as education, employment, food/shopping, and healthcare is an important goal for transit planners. The factor levels of some of the demographic groups were further analyzed to examine the equality between them in regards to travel times and travel speeds.

Following is a series of graphs and charts to help further highlight the inequalities that existed between the different sociodemographic groups when traveling to specific destinations. Figures 67–72, all highlight how each factor level of the different social groups compared to the reference factor level of that social group to the specific destination. As mentioned above, a value of 1 indicated that there was no difference in travel times between the specific factor level and the reference factor level, while a value above 1 indicated that the specific factor level in the social group tended to have higher

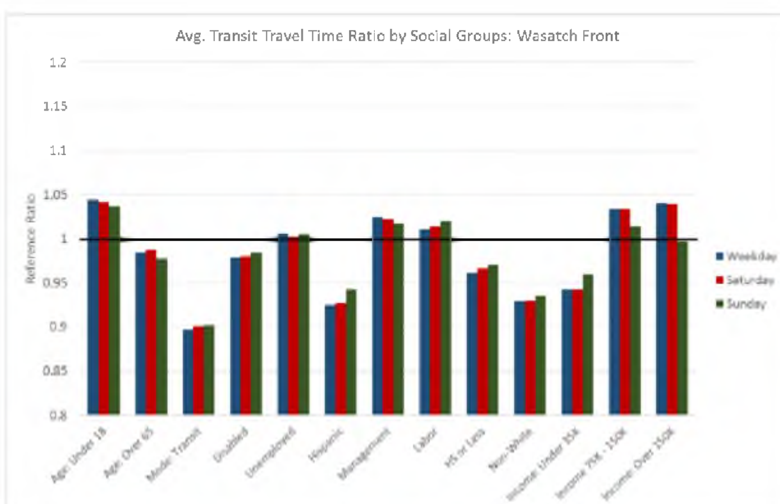


Figure 66: Travel time equality by social group for entire study area.

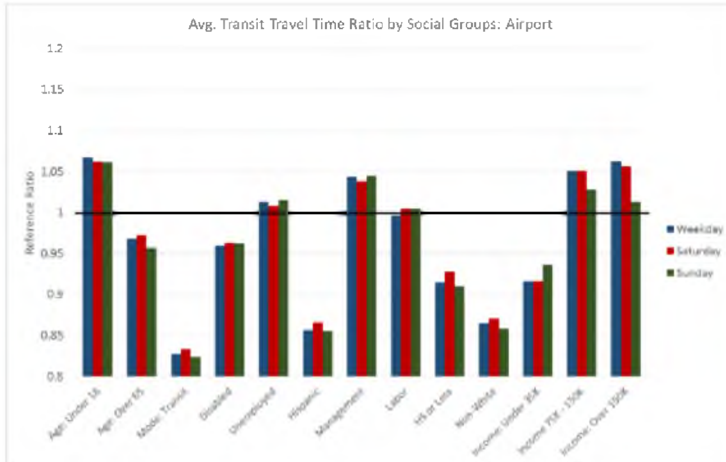


Figure 67: Travel time equality by social group to the Salt Lake Intl' Airport.

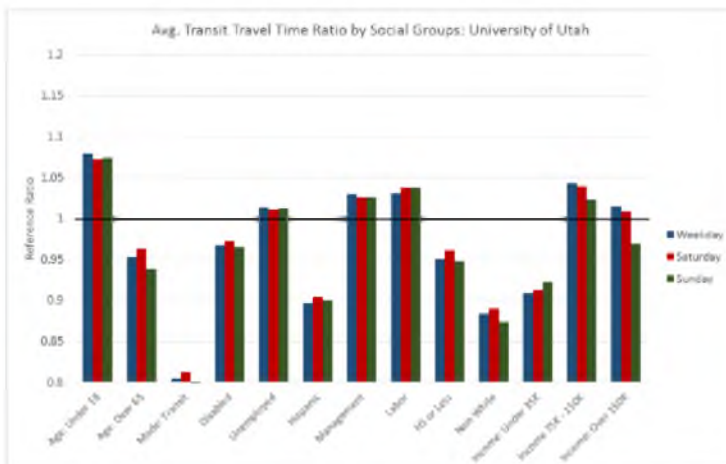


Figure 68: Travel time equality by social group to the University of Utah.

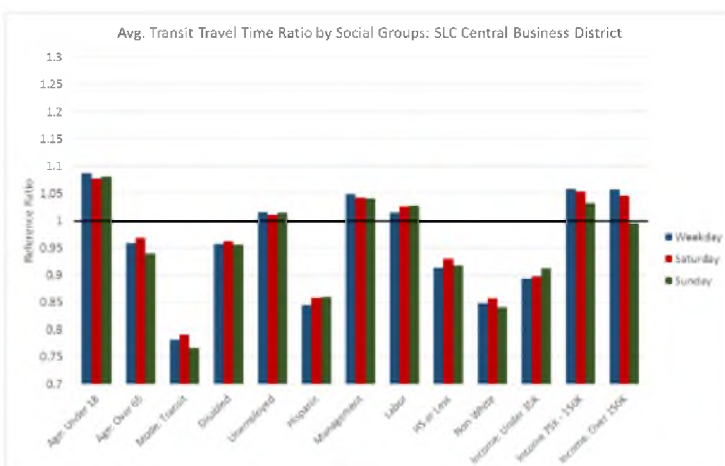


Figure 69: Travel time equality by social group to the SLC Central Business District.

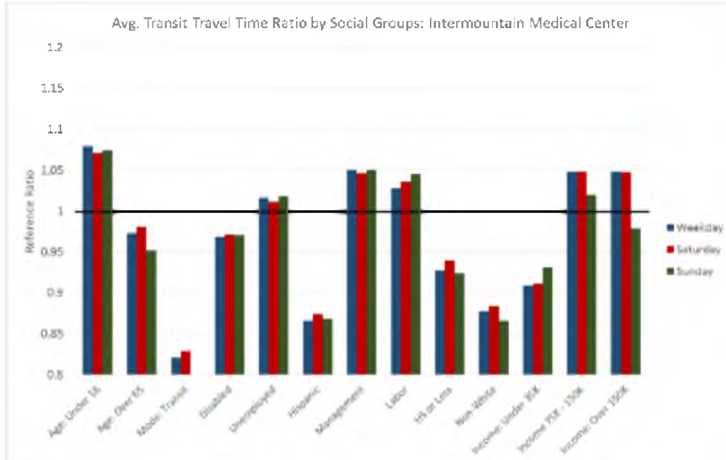


Figure 70: Travel time equality by social group to the Intermountain Medical Center.

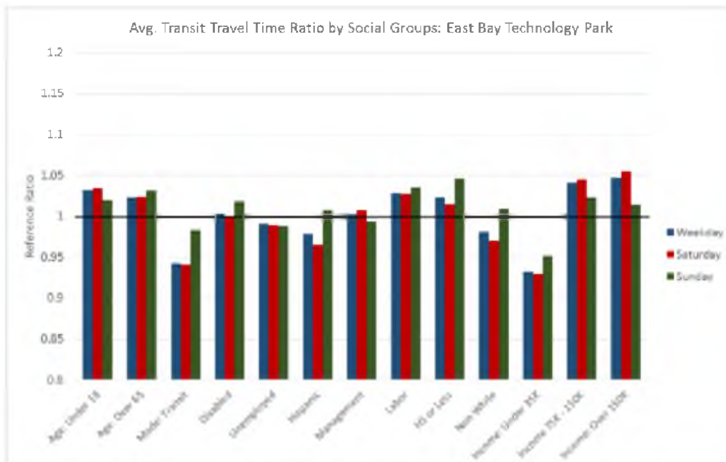


Figure 71: Travel time equality by social group to the East Bay Technology Park.

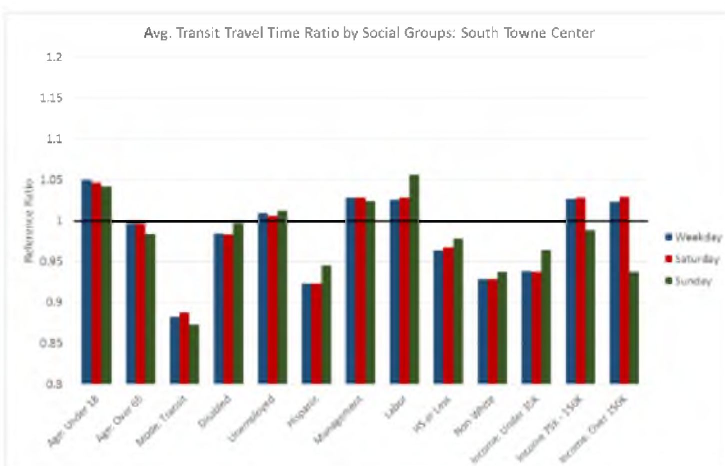


Figure 72: Travel time equality by social group to the South Towne Center.

travel times than the reference factor level and a value below 1 indicated the opposite (lower travel times than the reference factor level).

After reviewing Figures 67–72, it was determined all of the destinations (with the exception of the East Bay Technology Park) had similar patterns when compared to the reference factor levels. These patterns were similar to what was seen when examining the entire study area, so they will only be discussed briefly. First, when looking at age, compared to those between 18 and 64, those under 18 tended to have higher travel times, while those over 64 tended to have lower travel times. However, the exception was that for East Bay Technology Park, both those under 18 and those over 64 had higher travel times than those that were 18–64. Disability status showed a similar trend. Compared to those that were not disabled, those that were disabled tended to have lower travel times. However, again for the East Bay Technology Park, those that were disabled actually had higher travel times than those that were not. The rest of the sociodemographic groups of interest, however, all showed the same patterns regardless of the destination that was examined. For race and ethnicity, those that were Hispanic had lower travel times compared to those that were non-Hispanic, while non-White individuals also had lower travel times compared to those that were White. Income had a few more factor levels than the demographic groups, but inequality was still witnessed. Compared to those individuals in households that made between $35,000 and $75,000, those in households that made less than $35,000 had lower travel times. By contrast, those in households that made over $75,000 tended to have higher travel times.

While examining the overall differences between social groups helped to highlight overall inequality issues, so too did the more specific analysis of examining the temporal trends in travel times that existed within the different social groups across the different days. Additional analysis was performed on some of those destinations, with Figures 73–87 specifically examining some of different sociodemographic groups, such as disability status and age, and highlighting how the travel times fluctuated over time between the different groups and with Tables 45–59 narrowing out the times when travel times were at their highest or lowest for each of the different sociodemographic group factor levels.

In addition, the last portion of the travel time analysis examined Figures 73–87 to provide a better understanding into the differences between the factor levels of the demographic groups. As before, most of the same trends were noticed for the different sociodemographic groups regardless of the destination. However, there were a few exceptions that will be discussed. First, those that were disabled tended to have lower travel times than those that were not disabled. For those travel times, the difference was around 5 minutes. However, for the South Towne Center destination (Figure 83), there was only a very minimal difference. Lastly, for the East Bay Technology Park (Figure 78), those that were disabled had higher travel times, being around 3 minutes above those that were not disabled. A similar pattern was seen for race and ethnicity. For race and ethnicity, White individuals had higher travel times than those that were non-White, and non-Hispanic individuals had higher travel times than those that were Hispanic. On average, the difference was close to 15 minutes for all of the destinations except East Bay Technology Park (Figure 80) and South Towne Center (Figure 85), in which the difference was closer to 4 minutes. For income, regardless of the destination, individuals in households that made less than $35,000 had average travel times around 7–10 minutes

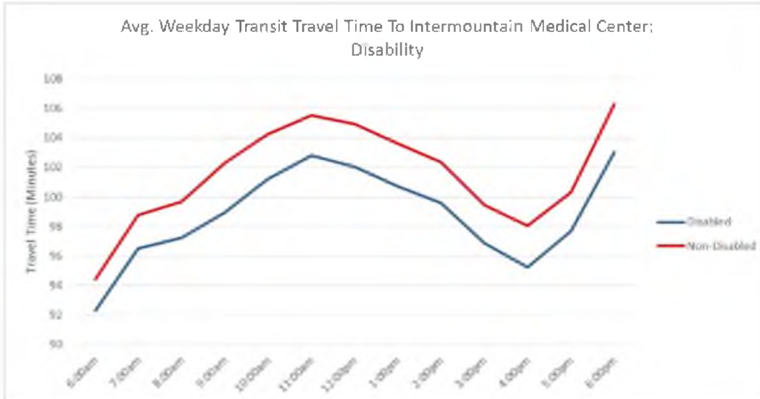


Figure 73: Travel times by disability status to the Intermountain Medical Center.

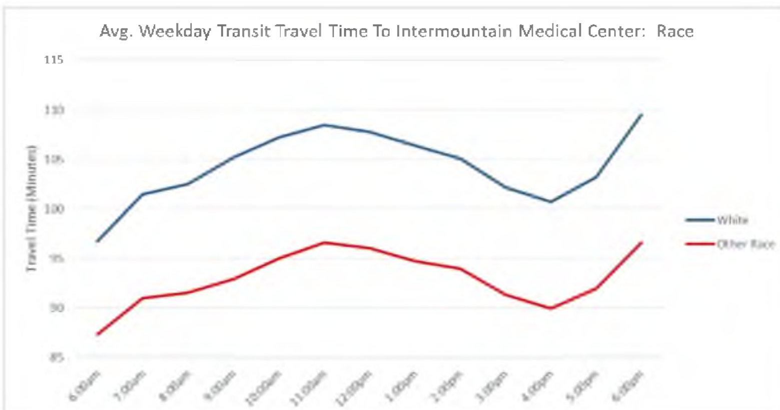


Figure 74: Travel times by racial status to the Intermountain Medical Center.

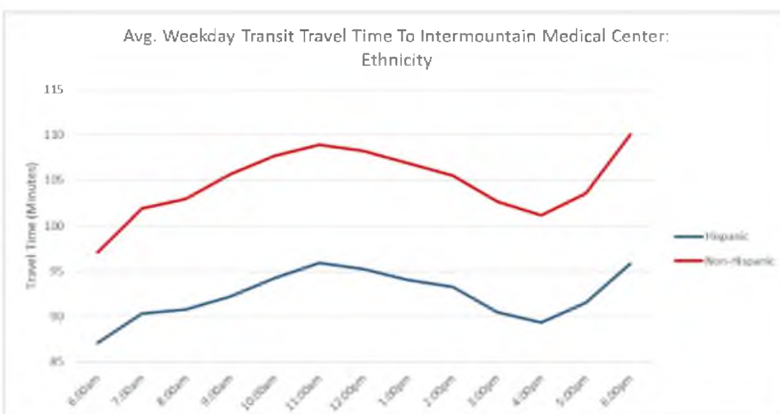


Figure 75: Travel times by ethnicity to the Intermountain Medical Center.

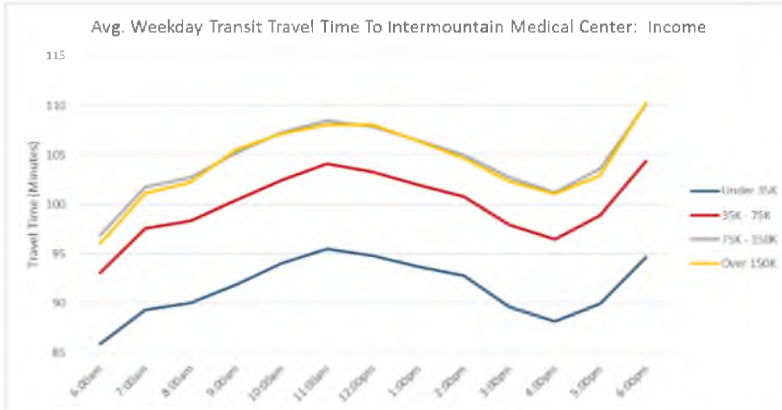


Figure 76: Travel times by household income to the Intermountain Medical Center.

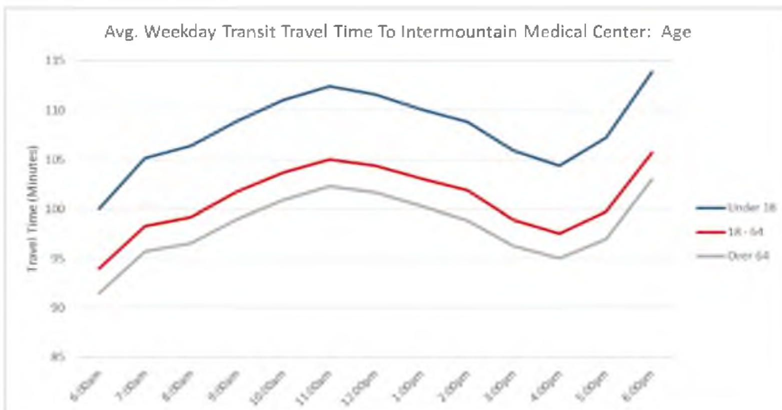


Figure 77: Travel times by age to the Intermountain Medical Center.

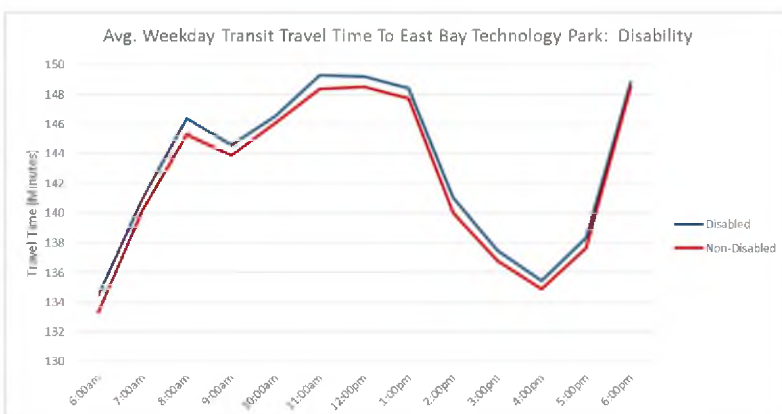


Figure 78: Travel times by disability status to the East Bay Technology Park.

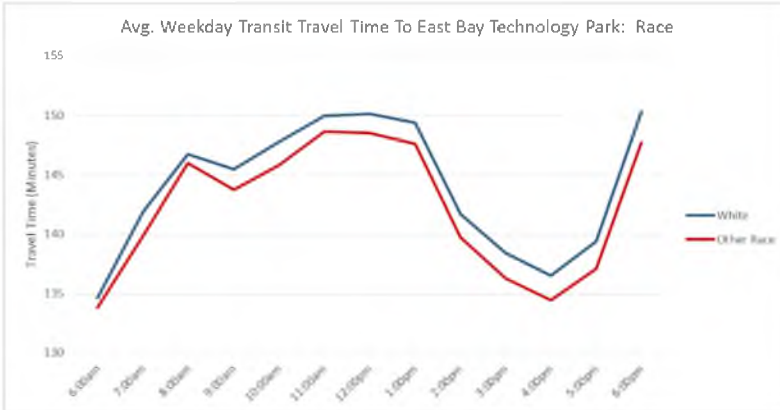


Figure 79: Travel Times by racial status to the East Bay Technology Park.

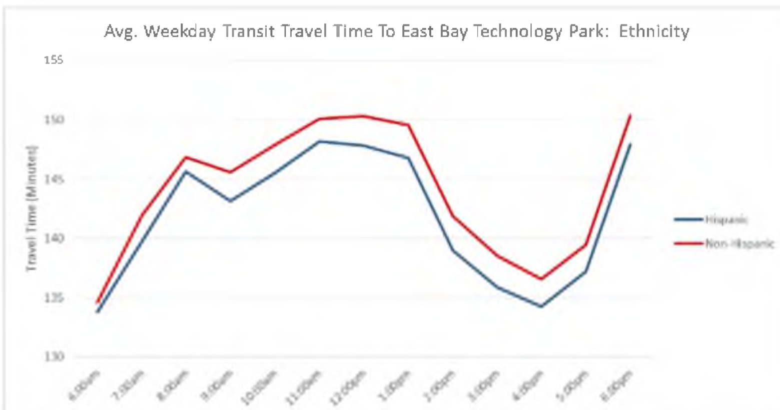


Figure 80: Travel times by ethnicity to the East Bay Technology Park.

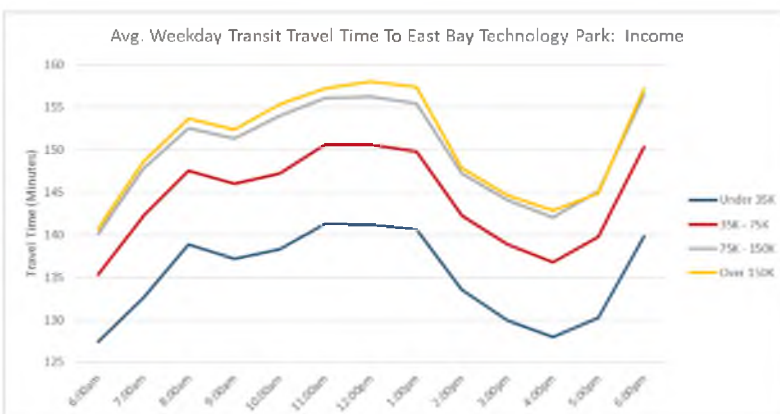


Figure 81: Travel times by household income to the East Bay Technology Park.

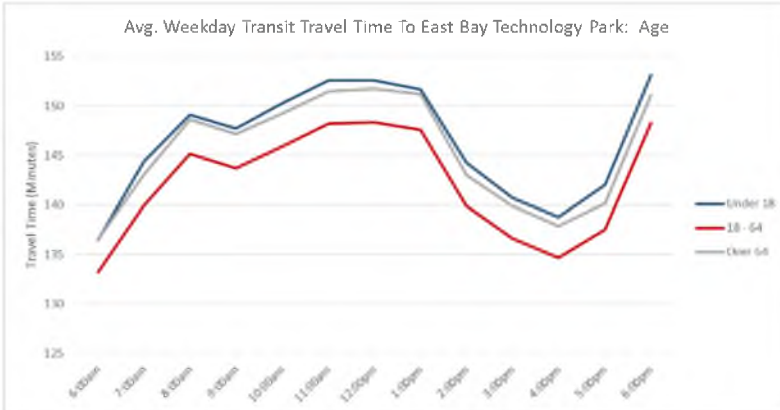


Figure 82: Travel times by age to the East Bay Technology Park.

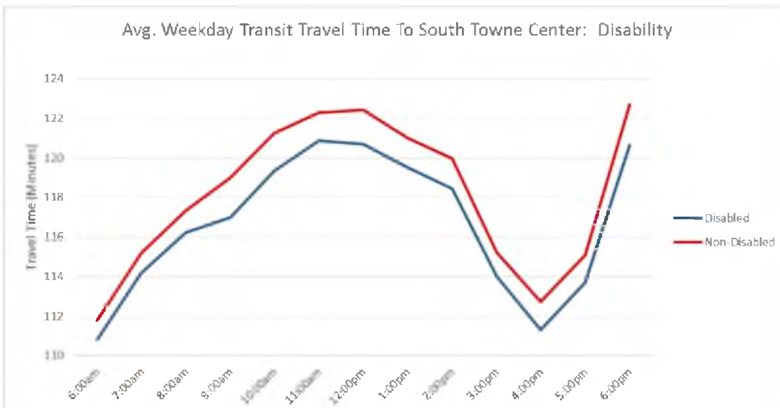


Figure 83: Travel times by disability status to the South Towne Center.

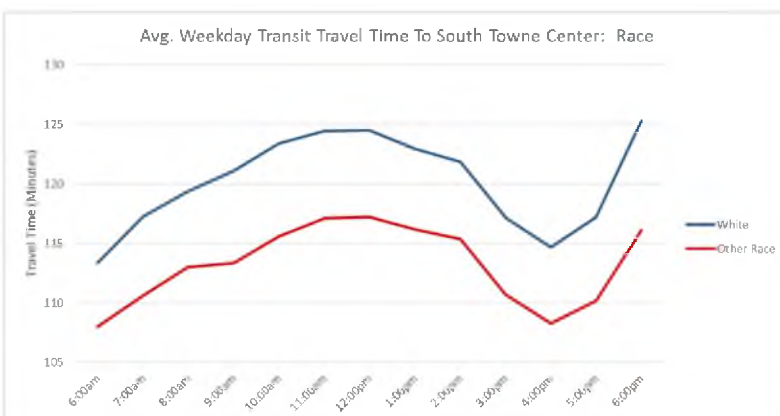


Figure 84: Travel times by racial status to the South Towne Center.

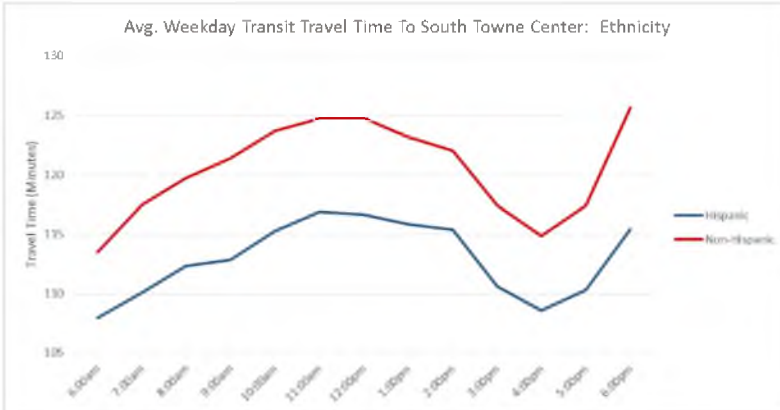


Figure 85: Travel times by ethnicity to the South Towne Center.

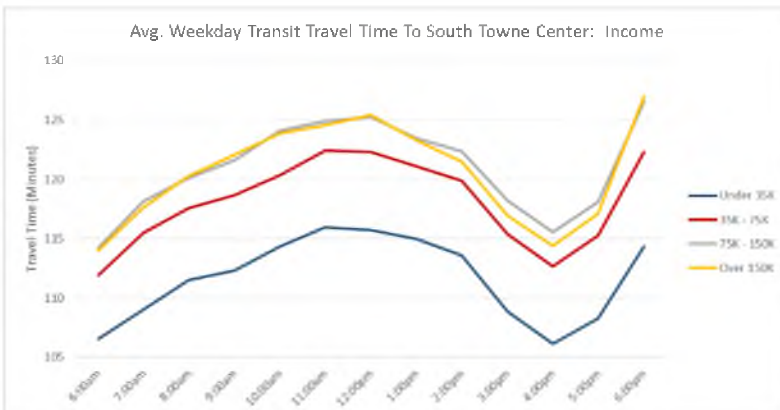


Figure 86: Travel times by income to the South Towne Center.

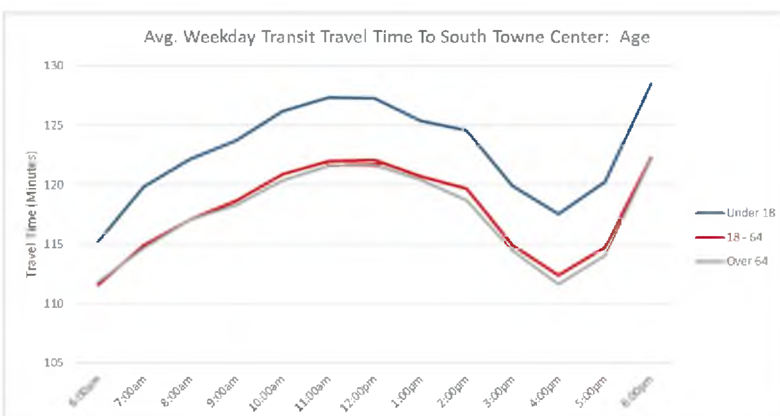


Figure 87: Travel times by age to the South Towne Center.

Table 45: High/low travel times by disability status to Intermountain Medical Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Disabled	6am; 4pm	11am
Nondisabled	6am; 4pm	11am

Table 46: High/low travel times by racial status to Intermountain Medical Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
White	7am; 4pm	10am
Other Race	7am; 4pm	11am

Table 47: High/low travel times by ethnicity to Intermountain Medical Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Hispanic	6am; 4pm	11am
Non-Hispanic	6am; 4pm	11am

Table 48: High/low travel times by household income to Intermountain Medical Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Less than 35K	6am; 4pm	11am
35K–75K	6am; 4pm	11am
75K–150K	6am; 4pm	11am
Over 150K	6am; 4pm	12pm

Table 49: High/low travel times by age to Intermountain Medical Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Under 18	6am; 4pm	11am
18–64	6am; 4pm	11am
Over 64	6am; 4pm	11am

Table 50: High/low travel times by disability status to East Bay Technology Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
Disabled	6am; 4pm	11–12am
Nondisabled	6am; 4pm	11–12am

Table 51: High/low travel times by racial status to East Bay Technology Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
White	6am; 4pm	12pm
Other Race	6am; 4pm	11am

Table 52: High/low travel times by ethnicity to East Bay Technology Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
Hispanic	6am; 4pm	11am
Non-Hispanic	6am; 4pm	12pm

Table 53: High/low travel times by household income to East Bay Technology Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
Less than 35K	6am; 4pm	11am–12pm
35K–75K	6am; 4pm	11am–12pm
75K–150K	6am; 4pm	11am–12pm
Over 150K	6am; 4pm	12pm

Table 54: High/low travel times by age to East Bay Technology Park.

	Low Travel Time Peaks	*High Travel Time Peaks*
Under 18	6am; 4pm	11am
18–64	6am; 4pm	12pm
Over 64	6am; 4pm	12pm

Table 55: High/low travel times by disability status to South Towne Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Disabled	6am; 4pm	11am
Nondisabled	6am; 4pm	12pm

Table 56: High/low travel times by racial status to South Towne Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
White	6am; 4pm	11am–12pm
Other Race	6am; 4pm	11am–12pm

Table 57: High/low travel times by ethnicity to South Towne Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Hispanic	6am; 4pm	11am
Non-Hispanic	6am; 4pm	12pm

Table 58: High/low travel times by ethnicity to South Towne Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Less than 35K	6am; 4pm	11am
35K–75K	6am; 4pm	11am
75K–150K	6am; 4pm	12pm
Over 150K	6am; 4pm	12pm

Table 59: High/low travel times by age to South Towne Center.

	Low Travel Time Peaks	*High Travel Time Peaks*
Under 18	6am; 4pm	11–12am
18–64	6am; 4pm	11–12am
Over 64	6am; 4pm	11–12am

less than those that made $35,000–$75,000. While both of the income groups above $75,000 had higher travel times, they alternated to the degree in which they did. However, on average, the higher income groups had travel times around 5 minutes higher, with the higher income groups being fairly similar with only a minute or less difference. Lastly, for age, a similar pattern for all of the destinations was seen. Those that were under 18 had travel times to all destinations about 7 minutes faster than those that were 18–64. Those that were over 64 had travel times around 3–5 minutes higher.

One final result of interest is that regardless of the sociodemographic group or the destination, each of the different sociodemographic groups depicted higher travel times and lower travel times at similar times of the day. When examining Tables 45–54 that depict the travel times for each of the different sociodemographic groups, the high travel time peaks consistently appeared between 11am and 12pm, and the lower travel time peaks appeared between 6 and 7am, and again around 4pm.

Examining the travel times, it was apparent that some differences were evident between some of the social groups. For example, those that had higher income also had higher travel times while those with lower income had lower travel times. While there is obviously an imbalance because both of the income groups do not have equal travel times, it is seen that lower income groups rely more heavily on the public transit as their main mode of transportation and therefore, for them it is more of a necessity while for those who have higher income and can afford private automobiles; it is seen more as a convenience. Therefore, it is argued that while there was some obvious inequality, depending on the situation, this inequality is actually seen favorably by transit and government agencies.

4.2.6 Sociodemographic Accessibility to Destinations (Speed)

As mentioned numerous times, it was important to examine travel speeds in order to account for the influence of geographic distance on the results. When examining the overall weighted average travel speed for the different sociodemographic groups, it can be seen in Figure 88 that some variation was present. The chart depicts how each factor level of the different social groups compared to the reference factor level of that social group. A value of 1 indicated that there was no difference in travel speed between the specific factor level and the reference factor level. A value above 1 indicated that the specific factor level in the social group tended to have higher travel speeds than the reference factor level, with a value below 1 indicating the opposite. As Figure 88 indicates, for the whole study area, average travel speeds seldom varied by more than 5% between social groups. This indicated a high level of equality in average travel speeds when examining all destinations.

It was also important to examine if these same levels of equality were present when considering specific destinations. In order to perform this analysis, each destination was examined using a similar graph to Figure 88. While most of the different sociodemographic groups for the different destinations had similar findings when it came to travel times, it was much different when comparing the travel speeds. When examining the airport (Figures 89), East Bay Technology Park (Figures 90), and South Towne Center (Figure 91), it was seen that those under 18 had lower travel speeds than those that were 18–64. The University of Utah (Figure 92), Intermountain Medical Center (Figure 93), and SLC Central Business District (Figure 94) had higher travel speeds than those aged between 18 to 64 years old. For all of the destinations except the East Bay

Figure 88: Travel speed equality by social group for the entire study area.

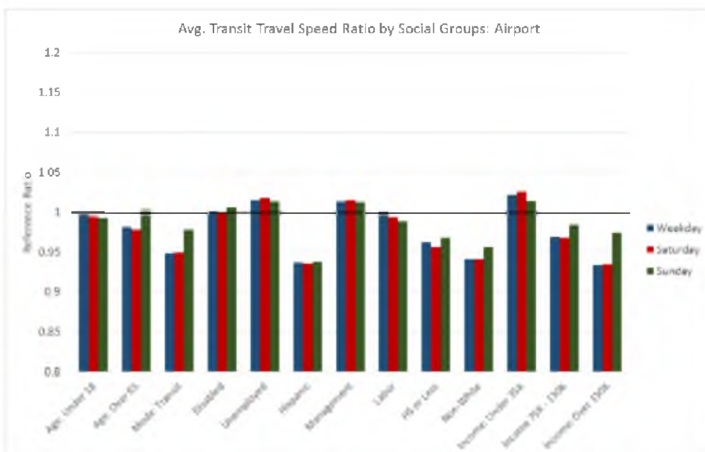


Figure 89: Travel speed equality by social group to the Salt Lake Intl' Airport.

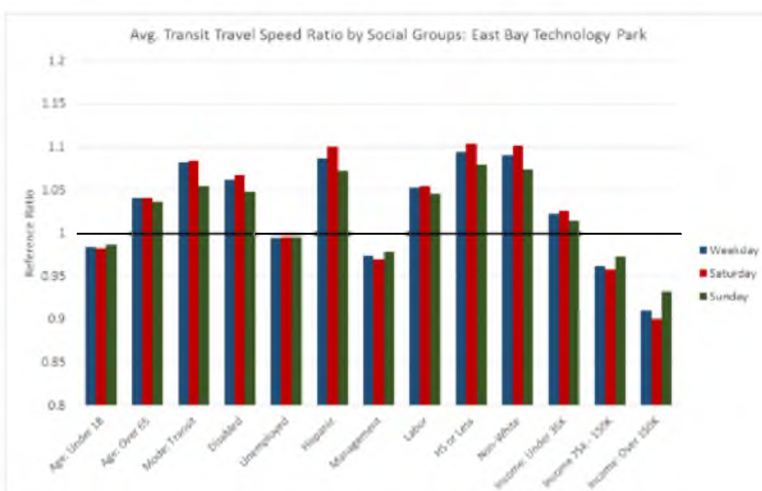


Figure 90: Travel speed equality by social group to the East Bay Technology Park.

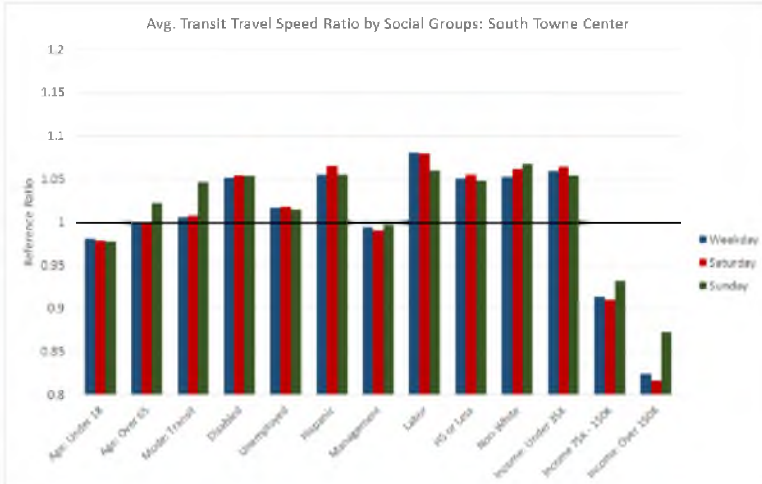


Figure 91: Travel speed equality by social group to the South Towne Center.

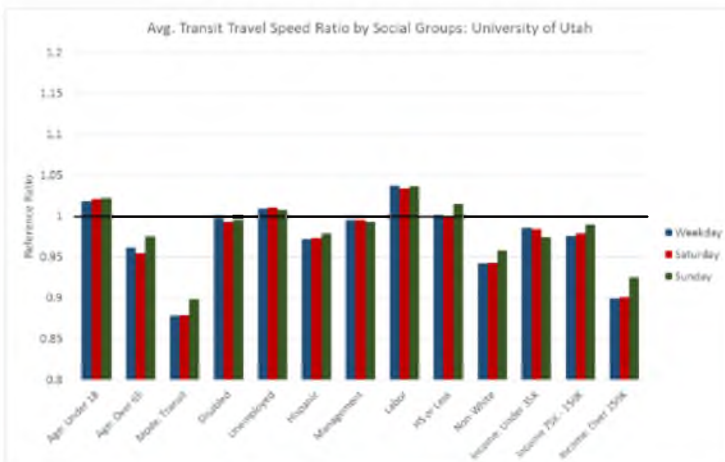


Figure 92: Travel speed equality by social group based on to the University of Utah.

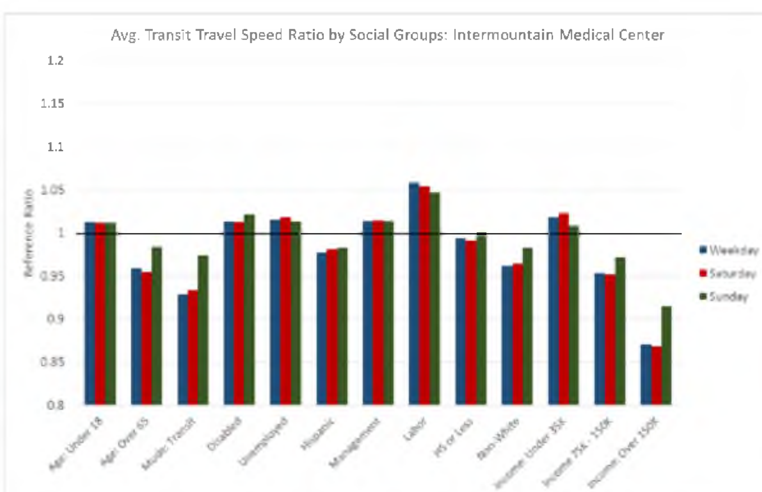


Figure 93: Travel speed equality by social group to the Intermountain Medical Center.

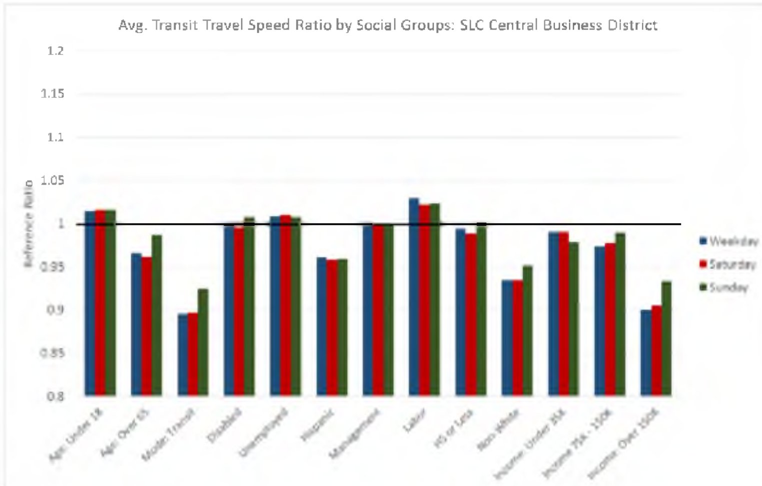


Figure 94: Travel speed equality by social group to the SLC Central Business District.

Technology Park (Figures 90), those over 65 had lower travel speeds.

Comparing disability status had a similar finding. For the East Bay Technology Park (Figures 90), South Towne Center (Figure 91), and Intermountain Medical Center (Figures 93), those that were disabled had higher travel speeds compared to those that were not disabled. However, the opposite was seen for the airport (Figure 89), the University of Utah (Figure 92), and the SLC Central Business District (Figure 94). Similar findings were found for both the ethnicity and racial demographic groups. Those that were Hispanic or non-White had lower travel speeds to the airport (Figure 89), the University of Utah (Figure 92), the Intermountain Medical Center (Figure 93), and the SLC Central Business District (Figure 94). By contrast, those same groups had higher travel speeds to the East Bay Technology Park (Figure 90) and to the South Towne Center (Figure 91). Lastly, overall the trends seen in the different income groups were similar for each destination (Figures 89–94). Those individuals whose households made less than $35,000 tended to have higher travel speeds than those that made between $35,000 and $75,000 to all of the destinations examined except for the University of Utah and the SLC Central Business District. However, no matter the destination, those that made over $75,000 had lower travel speeds.

As mentioned throughout this section, the travel times and the travel speeds showed somewhat similar findings. For example, the lower income groups tended to have lower travel times and higher travel speeds, while the higher income groups had higher travel times with lower travel speeds. Similar to the travel times, differences were present between the income groups in regards to travel speeds. Again, it is argued that the transit network was performing as hoped when the travel times were lower and travel speeds were higher for the lower income groups compared to the higher income groups.

Regardless of the sociodemographic group or the destination, each of the different sociodemographic groups depicted higher travel speeds and lower travel speeds at similar times (see Tables 60–70). When examining the graphs that depict the travel speeds for each of the different sociodemographic groups, the higher travel speed peaks consistently appeared around 6 and 7am and again around 4pm, and the lower travel speed peaks appeared later in the morning, around 10–11am.

Lastly, when examining more closely the different sociodemographic groups and each variable, a more complete trend was seen. First, for disability status, the travel speeds were fairly similar for those that were disabled or nondisabled when traveling to all of the destinations examined (Figures 95–98). White individuals tended to have around 0.5 MPH higher speed than those that were a different race (no figures shown). A similar finding was seen for those that were non-Hispanic having around 0.5 MPH higher travel speeds than those that were Hispanic (Figures 99–103). Those individuals with a household income either under $35,000 or between $35,000 to $75,000 tended to have

Table 60: High/low travel speeds by age to the Salt Lake Intl' Airport.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Under 18	10–11am	6am; 4pm
18–64	10–11am	6am; 4pm
Over 64	10–11am	6am; 3–4pm

Table 61: High/low travel speeds by disability status to the University of Utah.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Disabled	11am	7am; 4pm
Nondisabled	10–11am	7am; 4pm

Table 62: High/low travel speeds by ethnicity to the University of Utah.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Hispanic	11am	6am; 4pm
Non-Hispanic	10–11am	6am; 4pm

Table 63: High/low travel speeds by disability status to Intermountain Medical Center.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Disabled	11am	6am; 4pm
Nondisabled	11am	6am; 4pm

Table 64: High/low travel speeds by ethnicity to Intermountain Medical Center.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Hispanic	11am	7am; 4pm
Non-Hispanic	11am	7am; 4pm

Table 65: High/low travel speeds by disability status to East Bay Technology Park.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Disabled	11am–1pm	6am; 4pm
Nondisabled	11am–1pm	6am; 4pm

Table 66: High/low travel speeds by ethnicity to East Bay Technology Park.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Hispanic	11am–1pm	6am; 4pm
Non-Hispanic	11am–1pm	6am; 4pm

Table 67: High/low travel speeds by age to East Bay Technology Park.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Under 18	11am–1pm	6am; 4pm
18–64	11am–1pm	6am; 4pm
Over 64	11am–1pm	6am; 4pm

Table 68: High/low travel speeds by disability status to SLC Central Business District.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Disabled	11am	6am; 4pm
Nondisabled	11am	6am; 4pm

Table 69: High/low travel speeds by ethnicity to SLC Central Business District.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Hispanic	11am	6am; 4pm
Non-Hispanic	11am	6am; 4pm

Table 70: High/low travel speeds by ethnicity to the South Towne Center.

	Low Travel Speed Peaks	*High Travel Speed Peaks*
Hispanic	11am	6am; 4pm
Non-Hispanic	11am–12pm	6am; 4pm

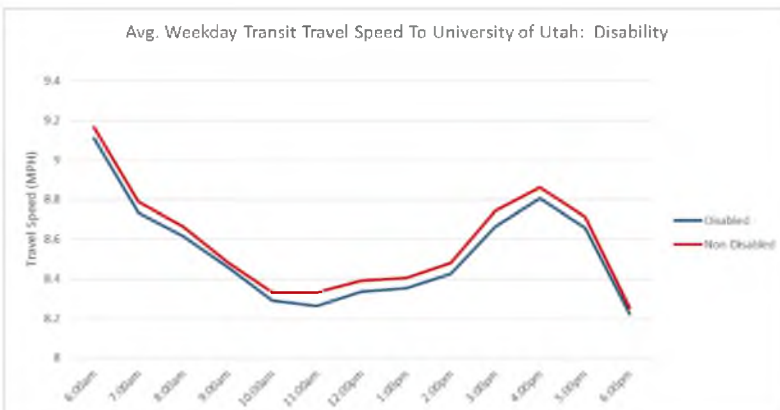


Figure 95: Travel speeds by disability status to the University of Utah.

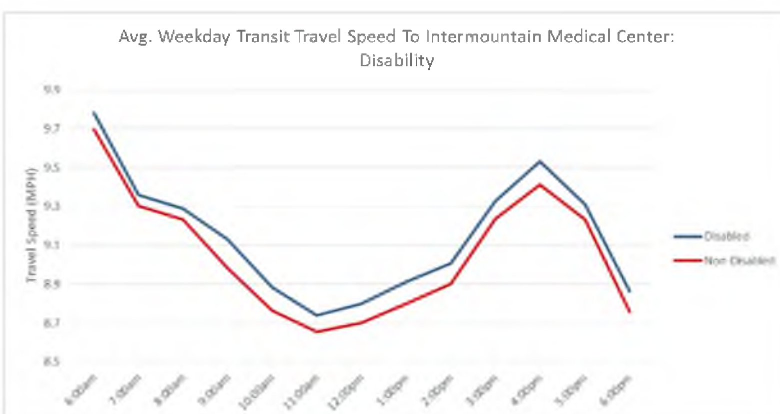


Figure 96: Travel speeds by disability status to the Intermountain Medical Center.

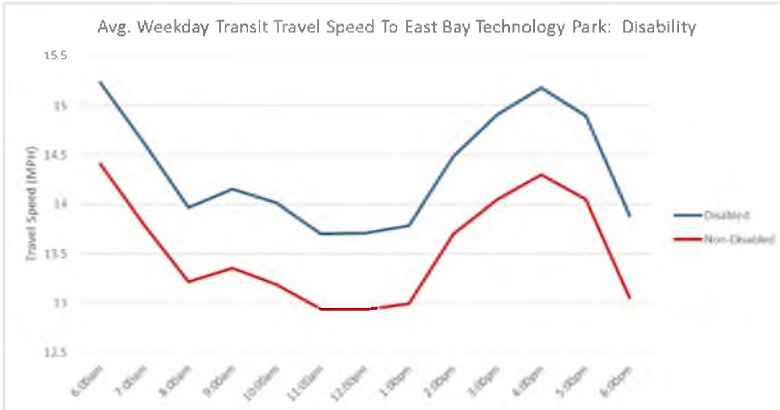


Figure 97: Travel speeds by disability status to the East Bay Technology Park.

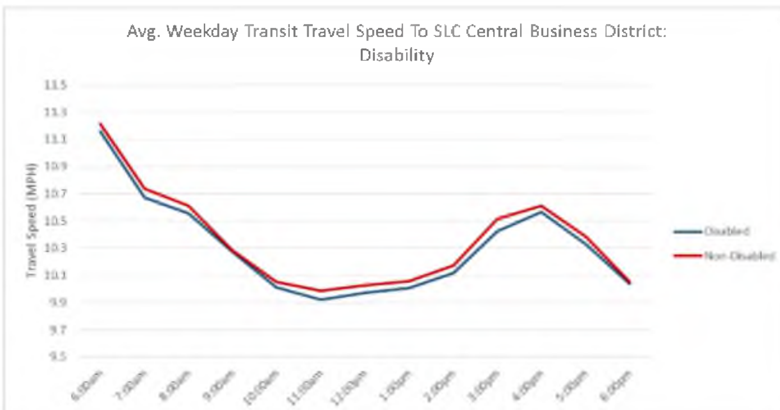


Figure 98: Travel speeds by disability status to the SLC Central Business District.

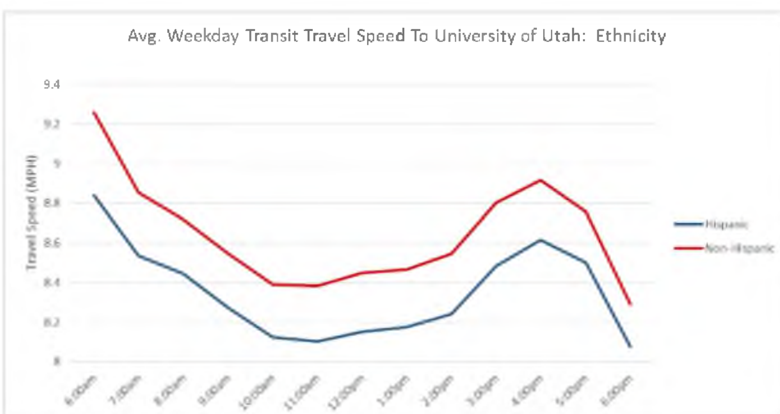


Figure 99: Travel speeds by ethnicity to the University of Utah.

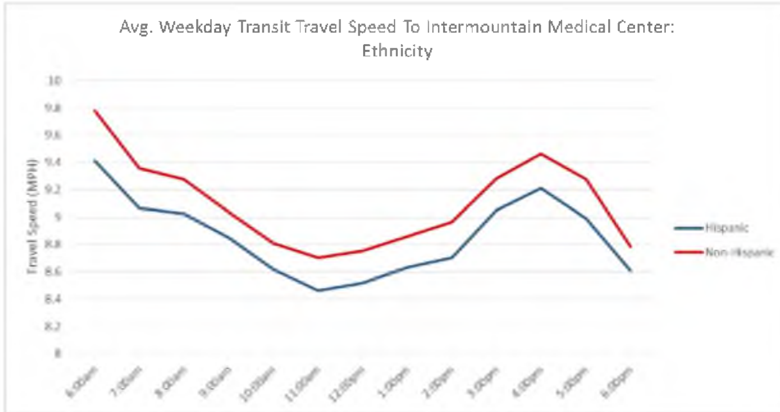


Figure 100: Travel speeds by ethnicity to the Intermountain Medical Center.

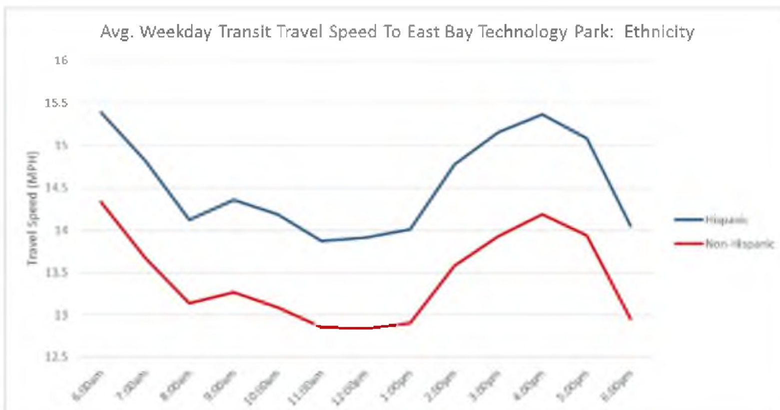


Figure 101: Travel speeds by ethnicity to the East Bay Technology Park.

Figure 102: Travel speeds by ethnicity to the SLC Central Business District.

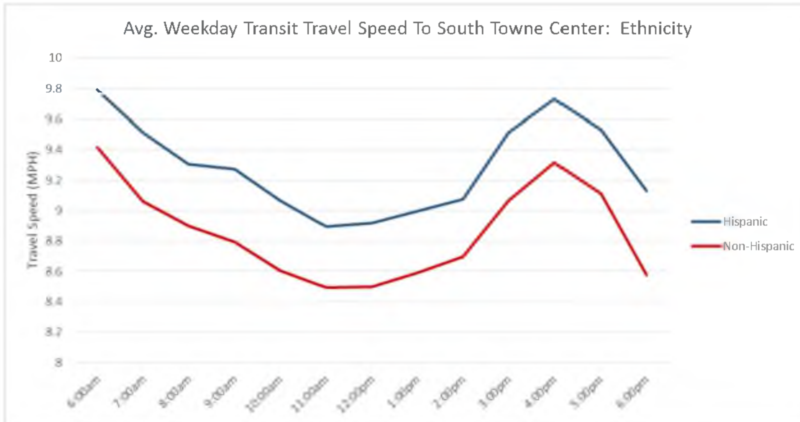


Figure 103: Travel speeds by ethnicity to the South Towne Center.

the fastest travel speeds (no figures shown), with both groups being fairly similar to each other with only around 0.2 MPH difference. Those that made between $75,000 and $150,000 were around 0.4 MPH slower than the lower income groups. Lastly, those that had a household income over $150,000 tended to be significantly slower by almost around 1 MPH.

By examining the transit travel times and the transit travel speeds, it was seen that while higher levels of inequality were witnessed when looking at the travel times, the level of inequality diminished greatly when examining the transit travel speeds. However, while the inequality diminished, the results still indicated that the transit network provided better service for some sociodemographic groups than others.

4.3 Adequacy of Supplying Sociodemographic Demand

The last major analysis for this research focused on the separate travel surveys that have been discussed previously. Each of the surveys contained trip details, with the Utah Household Travel Survey containing information about any type of walking, biking, driving, or transit trip. However, the UTA survey only took into account transit trips that were made. The purpose of this part of the analysis was to determine how well the transit network schedule provided service for the trip demands of the different social groups based on actual trip information.

4.3.1 Travel Times and Speeds—Utah Household Travel Survey

As is seen in Table 71, travel times for some sociodemographic factors were significantly different than others in regards to how well the public transit network supplied service when those types of individuals typically demanded travel. As can be easily seen in Table 71, all of the travel time ANOVAs were significant at the 0.05 level except for race and presence of driver's license. However, when examining travel speed (Table 72), it was seen that a few more of the variables were considered to not be significant, with those being Hispanic, race, presence of driver's license, limited mobility, and income.

The series of Tables (71 and 72) also contain the average Z-Scores for the factor levels of each of the significant sociodemographic factors noted above. While the ANOVA test proved that at least one of the changes between those factors were significant, ANOVA did not determine which factor levels were the reason for the difference. These tables were only being used for visual preliminary analysis.

As mentioned previously, the results of the Z-score showed how well the transit network provided service for when those of that sociodemographic factor level actually traveled based on the travel surveys. Negative numbers indicated that on average, those of that particular sociodemographic group traveled at times when the public transit travel time of their trips were below the average travel times when the network was in operation (5am–10pm). By contrast, positive numbers indicated that on average, those of that particular variable traveled at times when the public transit travel time of their trips were

Table 71: Utah Household Travel Survey Residential (A), Demographic (B), and Demographic/Travel (C) Results—Time.

(A)		***Z-Score***
Res. Type	***Other***	-0.666
	< 3 Apts.	-0.209
	Townhouse	-0.106
1.72e-06 ***	***Single Family***	-0.091
	Mobile	-0.082
	Dorm	-0.067
	Multi-Family	-0.053
	> 4 Apts.	0.030
Years at Res.	***>20***	-0.271
	16–20	-0.168
	11–15	-0.089
1.7e-06 ***	***1–5***	-0.069
	6–10	-0.060
	< 1	0.028
Place Type	***Other***	-0.271
	Small Town	-0.168
1.7e-06 ***	***Suburbs (House)***	-0.089
	City Residential	-0.069
	Suburbs (Mix)	-0.060
	City Downtown	0.028

(B)		***Z-Score***
Income	***Over 250K***	-0.124
	200K–250K	-0.122
	75K–100K	-0.117
	150K–200K	-0.100
0.0091 **	***100K–150K***	-0.088
	50K–75K	-0.085
	35K–50K	-0.054
	25K–35K	-0.030
	10K–25K	-0.014
	Under 10K	0.034
Education	***Graduate Degree***	-0.124
	Bachelors	-0.098
	Technical	-0.090
6.4e-05 ***	***Some College***	-0.045
	Associates	-0.033
	HS Diploma	-0.027
	Less than HS	-0.021
Employ. Status	***Retired***	-0.137
	Full-Time	-0.115
	Homemaker	-0.056
1.56e-12 ***	***Not-employed***	-0.046
	Self-employed	-0.030
	Part-Time	-0.014
	Student (<25)	0.042
	Student (>25)	0.086
Gender	***Male***	-0.099
0.00332 **	***Female***	-0.060
Hispanic	***Not-Hispanic***	-0.083
0.0104 *	***Hispanic***	0.002
	N/A	0.013

(C)		***Z-Score***
Age	***75–84***	-0.169
	85 +	-0.158
	65–74	-0.133
2.65e-14 ***	***45–54***	-0.108
	55–64	-0.097
	35–44	-0.089
	25–34	-0.068
	18–24	0.092
Trip Purpose	***HBW***	-0.277
	NHBW	-0.254
	HBPb	-0.173
	HBSch	-0.144
<2e-16 ***	***NHBNW***	-0.044
	HBShp	-0.016
	HBO	0.151
Travel Time	***Peak***	-0.505
<2e-16 ***	***Off-Peak***	0.224
Mobility	***Limited Mob.***	-0.128
0.00981 **	***No Limited Mob.***	-0.079
	N/A	0.181

Table 72: Utah Household Travel Survey Residential (A), Demographic (B), and Demographic/Travel (C) Results—Speed.

(A)		***Z-Score***
Res. Type	***Other***	0.573
	< 3 Apts.	0.204
	Mobile	0.187
0.00211 **	***Townhouse***	0.131
	Single Family	0.109
	Multi-Family	0.015
	> 4 Apts	-0.009
	Dorm	-0.018
Years at Res.	***16–20***	0.157
	<20	0.156
	11–15	0.115
0.0324 *	***1–5***	0.093
	6–10	0.072
	> 1	-0.019
Place Type	***Small Town***	0.157
0.0324 *	***Other***	0.156
	Suburb (Houses)	0.115
	City Residential	0.093
	Suburbs (Mix)	0.072
	City Downtown	-0.019

(B)		***Z-Score***
Income	***200k-250k***	0.232
	Over 250k	0.156
	75K–100K	0.141
	150K–200K	0.123
0.0504 .	***100K–150K***	0.102
	50K–75K	0.101
	25k-35k	0.069
	35k-50k	0.062
	10K–25K	0.035
	Under 10K	-0.056
Education	***Graduate Degree***	0.173
	Vo-Tech	0.116
	Bachelors	0.114
1.73e-05 ***	***> HS***	0.051
	Associates	0.050
	HS Diploma	0.046
	Some College	0.032
Employ. Status	***Retired***	0.211
	Full-Time	0.120
	Not-employed	0.090
	Homemaker	0.089
7.9e-10 ***	***Self-employed***	0.052
	Part-Time	0.007
	Student (<25)	-0.039
	Student (>25)	-0.105
Gender	***Male***	0.122
0.00728 **	***Female***	0.073
Hispanic	***Not-Hispanic***	0.100
0.0701 .	***N/A***	0.077
	Hispanic	-0.015

(C)		***Z-Score***
Age	***85+***	0.280
	75–84	0.253
	65–74	0.190
2.89e-12 ***	***55–64***	0.128
	45–54	0.127
	35–44	0.094
	25–34	0.069
	18–24	-0.098
Trip Purpose	***HBW***	0.331
	NHBW	0.289
	HBSch	0.222
	HBPb	0.212
<2e-16 ***	***NHBNW***	0.067
	HBShp	-0.016
	HBO	-0.170
Travel Time	***Peak***	0.639
<2e-16 ***	***Off-Peak***	-0.289
Mobility	***Limited Mob.***	0.124
0.265	***No Limited Mob.***	0.096
	N/A	-0.100

above the average travel times for the entire day. Reviewing both the travel times and the travel speeds, not taking into consideration the significance values, it was seen that in regards to both travel time and travel speed, the same trends were seen for the variables in each sociodemographic group. The results of the travel time and travel speed analysis for each variable are as follows.

4.3.1.1 Age

Older individuals (those aged 75 and over) traveled when transit service provisions were at a higher level. This might have some relevance to the transit network providing better service for those that are retired. However, because this research examined inequality, the potential travel behavior reasons for this finding are not discussed. The middle-aged group was provided the next best level of service. This group typically consists of the working population. Lastly, those that were under 25 tended to be supplied with the worst transit service, with this age group typically consisting of students. Therefore, those of working age, as seen before, tended to be provided with the best transit service while those of student age were provided with the worst.

4.3.1.2 Ethnicity

For this variable, the two variables that were examined included Hispanic or non-Hispanic. The results indicated that those that were non-Hispanic were typically supplied better transit service than those that are Hispanic.

4.3.1.3 Income

Those with higher household incomes tended to be provided with better transit service compared to those with lower household incomes. This was seen by those that made over $250,000 being provided the best service in regards to below average travel times, while those that made less than $10,000 were provided the worst level of service.

4.3.1.4 Gender

Males were provided slightly better service than females in regards to transit.

4.3.1.5 Employment Status

The public transit network tended to supply better transit service for those that were retired or employed full-time, part-time, or self-employed. In contrast, poorer service was typically provided for students.

4.3.1.6 Educational Attainment

The highly educated individuals were also supplied with the better transit service than those that had a lower level of education. The results indicated that those with graduate or Bachelor degrees were provided the best level of service, while those that only had a high school diploma or GED, or else no high school diploma at all, were provided the worst service.

4.3.1.7 Mobility Status

Those that had limited mobility were provided with better transit service than those without limited mobility.

4.3.1.8 Peak Travel

Those that took peak trips were provided with better transit service compared to those that traveled during off-peak times. Again this would make sense because peak times were when the transit network (and most transit networks) tended to be the most optimal in order to provide the best level of service for those that use the network for work, but neglected those that travel during the day for other types of activities.

4.3.1.9 Trip Purpose

The transit network tended to provide the best service for those that traveled to or from work. The same was also seen for those that traveled for business, school, or shopping, but to a much lesser extent. The trips that were taken from home for an "other" type of purpose were provided with the worst transit service. It is expected that the transit network would be designed for those that are traveling for work, business related activities, or school rather than for other miscellaneous activities. Therefore, those that travel for different reasons than the main purposes, and therefore most likely rely on public transit for all of their trips, are provided with an unequal level of service than those that might only travel for convenience to avoid traffic or parking.

4.3.1.10 Type of Residence

Those of a more middle class living situation tended to perform trips when the public transit network was providing optimal service (such that the trip travel time would be below average). For example, those in apartments with less than three units, townhouses, and single family houses were more likely to travel during faster provision times. In contrast, those that lived in dorms on large apartment complexes tended to take trips when the public transit network was providing poorer service.

4.3.1.11 Number of Years Living at Current Residence

Typically the longer the person had lived at their current place of residence, the more trips that were taken during times when the trip travel time was below average. For example, those that lived at their current residence over 20 years had taken the most trips at times when trip times were below average. In contrast, those that lived in their residence for less than a year took more trips during times when the trip travel time was above average.

4.3.1.12 Place Type

Those living in residential areas, such as a small town, suburbs with houses only, city residential, and mixed-use suburbs tended to travel during higher level service periods. Those living downtown though tended to travel at times supplied with poorer transit service.

These results show that based on the Utah Household Travel Survey, inequality is present among the different factor levels in the sociodemographic groups. The most important examples being that those that had a higher household income generally traveled when the transit network was providing the best service compared to those that had lower household incomes. The problem is that those that have higher household incomes might have access to private automobiles but just take transit discretionarily, while those that are less affluent might not be able to afford a car and therefore might rely on public transit. A similar finding was noticed when examining educational attainment, with those that were more educated (and therefore might have a better paying job) traveling when the transit service was good, compared to those that were less educated traveling at times when the transit network was poorer.

4.3.2 Travel Times and Speeds—UTA Onboard Survey

After examining the Utah Household Travel Survey of all types of trips, the UTA Onboard survey, which contains only transit trips, was analyzed in a similar fashion. Though both of the surveys contained a variety of demographic characteristics, those that overlapped both of the surveys tended to produce similar findings, lending credibility to the discoveries made. Similarly to Tables 71 and 72, Tables 73 and 74 combine the ANOVA results (for example, 5.58e-11 *** for the "frequency" factor) and the Z-score results.

As is seen in Tables 73 and 74, the ANOVA results indicated that transit travel times and speeds were significantly different between population subgroups. All grouping factors were significant except gender, indicating inequality in service provision. The average Z-Scores for variables of each of the significant sociodemographic factors are also depicted in Tables 73 and 74. While the ANOVA test suggested that at least one of the differences between these factors were significant, these tables did not indicate the responsible factor levels. As was done for the Utah Household Survey discussed prior, because of the similarities between the travel times and the travel speeds in regards to the differences in service provided to the different sociodemographic groups, they will be discussed together.

4.3.2.1 Age

Again, the results for age are similar to those in the Utah Household Travel Survey. Older individuals tended to be provided with better transit service than the younger age groups. The results showed that all of the better service was provided for those over 25 years old, with those under 25 years old being provided the poorer service.

As mentioned previously, this might be the result of the older individuals being workers and the younger individuals being students and how these different groups tend to travel.

4.3.2.2 Household Income

A similar finding to that of the Utah Household Travel Survey was observed. Individuals in households with a higher income tended to be provided with better transit service. As income decreased, so too did the level of service, with the better service being provided to those in household where the income was over $75,000 and the poorer service supplied to those in households where the income was less than $15,000.

4.3.2.3 Primary Transit Mode

The results indicated that for transit mode, trips made using FrontRunner were often those provided with the best service. The reasoning behind this is that because FrontRunner service is fairly limited, it is only in operation typically during the peak travel periods and therefore, most of the FrontRunner trips are peak trips. Buses showed a similar finding. Depending on the route, buses might begin operation later in the morning and also end earlier in the evening. As a result, most trips occurred only during peak times. However, TRAX tended to run earlier in the morning and later in the evenings and therefore could be used for more off-peak trips.

4.3.2.4 Fare Type

Those using senior passes tended to be provided with the best transit service. Those with annual passes and adult passes also received fairly good transit service, most likely due to the fact that they might be used by workers during peak travel times. Students, one-way fares, and cash fares, which might be students traveling to school

Table 73: UTA Demographic (A) and Travel (B) Result—Time.

		Z-Score
Frequency	***5 Days***	-0.464
	4 Days	-0.457
	3 Days	-0.437
	1 Day	-0.370
5.58e-11 ***	***2 Days***	-0.356
	First Time	-0.315
	6 Days	-0.295
	Less than 1 / week	-0.207
	7 Days	-0.172
Age	***45–64***	-0.493
	65 +	-0.439
2.36e-08 ***	***25–44***	-0.413
	18–24	-0.301
Licensed	***Licensed***	-0.425
5.85e-05 ***	***Not Licensed***	-0.271
Income	***Over 75K***	-0.549
	50K–75K	-0.451
	35K–50K	-0.391
1.25e-15 ***	***25K–35K***	-0.339
	15K–25K	-0.306
	Less than 15K	-0.276
Trip Type	***HBW***	-0.534
	HBColl	-0.341
<2e-16 ***	***NHB***	-0.303
	HBO	-0.177
Number of Vehicles	***4 + Vehicles***	-0.485
	3 Vehicles	-0.485
	2 Vehicles	-0.468
1.21e-12 ***	***1 Vehicle***	-0.351
	None	-0.221

		Z-Score
Fare type	***Senior***	-0.534
	Ed/Eco/Annual	-0.532
	Adult	-0.481
	Discounted	-0.333
	Student	-0.330
<2e-16 ***	***One-Way***	-0.326
	Cash	-0.275
	Medicaid	-0.270
	Reduced Fare	-0.257
	Day/Group	-0.187
	Free Fare	-0.132
Egress Mode	***Drove***	-0.496
7.84e-05 ***	***Walk***	-0.394
	Bike	-0.265
Ingress Mode	***Drove***	-0.462
0.00067 ***	***Walk***	-0.389
	Bike	-0.273
Mode	***FrontRunner***	-0.537
	Bus	-0.527
2e-16 ***	***N/A***	-0.524
	TRAX	-0.277

Table 74: UTA Demographic (A) and Travel (B) Result—Speed.

		Z-Score
Frequency 8.89e-15 ***	***5 Days***	1.096
	4 Days	1.095
	3 Days	0.927
	First Time	0.879
	2 Days	0.830
	1 Day	0.788
	6 Days	0.726
	7 Days	0.470
	Less than 1 / week	0.273
Age 5.86e-11 ***	***45–64***	1.154
	65 +	0.986
	25–44	0.979
	18–24	0.636
Licensed 1.46e-05 ***	***Licensed***	0.985
	Not Licensed	0.592
Income 8.62e-13 ***	***Over 75K***	1.239
	50K–75K	1.033
	35K–50K	0.959
	25K–35K	0.738
	15K–25K	0.706
	Less than 15K	0.660
Trip Type <2e-16 ***	***HBW***	1.272
	HBColl	0.746
	NHB	0.638
	HBO	0.420
Number of Vehicles 2.02e-07 ***	***4 + Vehicles***	1.082
	2 Vehicles	1.074
	3 Vehicles	1.020
	1 Vehicle	0.854
	None	0.587

		Z-Score
Fare type	***Ed/Eco/Annual***	1.214
	Adult	1.170
	Senior	1.046
	One-Way	0.880
<2e-16 ***	***Student***	0.761
	Discounted	0.741
	Medicaid	0.709
	Cash	0.579
	Free Fare	0.419
	Day/Group	0.406
	Reduced Fare	0.404
Egress Mode 0.00615 **	***Drove***	1.082
	Walk	0.926
	Bike	0.635
Ingress Mode 0.00202 **	***Drove***	1.062
	Walk	0.900
	Bike	0.655
Mode	***FrontRunner***	1.295
	Bus	1.125
<2e-16 ***	***N/A***	0.979
	TRAX	0.692

during off-peak times were provided with slightly poorer service. Lastly, those who used Medicaid, reduced fare, and free fare were provided the worst service. Therefore, it appears that those who can afford the more expensive transit fares, such as annual and adult passes were provided with the best service, while those with discounted passes or free fare trips were provided with poorer service.

4.3.2.5 Trip Frequency

Those that took public transit 5 days a week (assumedly for work) tended to be provided with the best public transit service. As the number of days decreased, such as to 4 and 3, so too did the extent of being better supplied by the public transit network. An interesting finding was that those that were provided with the worst transit service were those that are infrequent transit riders, as well as those that take transit 6 or 7 times a week. Therefore, those that might typically rely on transit for work were provided with the best service, while those that might make a special trip once in a while, or else rely on public transit every day for all types of trips, were provided with poorer service.

4.3.2.6 Presence of Driver's License

The public transit network tended to provide better service for those that that had a driver's license, compared to those that did not. Those with a driver's license were most likely taking transit for convenience to bypass traffic or parking, while those that did not have a driver's license most likely rely on the network for all trips at various times of the day. As a result, the public transit network appears to provide better service to discretionary users compared to those who depend on the service.

4.3.2.7 Trip Purpose

Trip purpose had similar effects in the two surveys. Work trips were provided with the best transit service since they are most likely taken during peak times. Trips to other locations, such as colleges and those listed as other locations (school, shops, restaurants, etc.), were taken during poorer service times, which would make sense because these trips happen more during off-peak times.

4.3.2.8 Number of Vehicles

Similar in relation to those individuals with a driver's license, those with a higher number of vehicles tended to be supplied with better transit service. As the number of vehicles decreased, so too did the level of service. An interesting finding was that those with the worst service were those that had no vehicles and relied solely on public transit. However, again this is probably because those with vehicles used transit for work and therefore travel during peak travel times, while those with no vehicles rely heavily on the transit network for all trips, during peak and off-peak hours.

4.3.2.9 Ingress/Egress

These factors represented the ingress (to) and egress (from) transit stop mode. As both tables show, those that tended to drive to and drive from transit stops were provided with the best service. Those that walked and biked to and from the transit stops were provided with poorer transit service.

As indicated previously, for those characteristics that overlapped between the different surveys, similar findings were found, such as for income and age, and will not be discussed further. However, some of the different characteristics showed interesting results. For example, those that relied on the public transit network the most, such as 6 or 7 days a week, tended to be provided poorer service than those that required transit 5 or less days a week. This finding seems to indicate that those that might use transit to commute to work due to its convenience actually travel at times when the service is better than those that rely on the transit network for all types of trips. A similar, and startling, finding was discovered when examining the level of transit service compared to the number of cars. The results indicated those with the most amount of cars traveled at times when the transit service was providing better service than those that have one or even no vehicle. Therefore, it appears the transit network provides better service for those that might not actually need the service, but poorer service for those that might heavily rely on the service.

5. CONCLUSIONS

The purpose of this research was to better understand how accessibility to destinations using public transit fluctuates during a typical weekday by examining a temporally dynamic public transit network. This research was able to examine how the temporal variations could be measured and visualized and how transit network supply and travel demand could be combined to highlight where and when social inequality occurred. This was completed by

1. Developing a method to compute, describe, and visualize accessibility on a temporally dynamic public transit network;
2. Using the results of this method to perform analyses about the study area, specific destinations, and specific trips;
3. Comparing the demographic characteristics of the populations of all of the origins to see the level of equality differences between these populations to specific destinations; and lastly,
4. Using data about the travel demand of different demographic groups to determine if they traveled at times when the transit network provided better or poorer service.

This work demonstrated how a public transit travel time cube could effectively be used to investigate accessibility. The cube consisted of public transit travel times from all block groups to all block groups with start times at every minute of the day. I constructed one cube for a representative weekday and additional cubes for Saturday and Sunday. By aggregating over different sets of origins and destinations, the research demonstrated several methods for assessing accessibility. First, and most generally, transit travel times were summarized over all origins and destinations in order to investigate temporal fluctuations in overall network quality. Following this, origin/destination pairs were classified by Euclidean distance and direction of travel in order to investigate spatial patterns in accessibility. Next came a series of analyses investigating connectivity between specific nodes of activity in the region. And lastly, the cube was fused with travel demand profiles from two recent travel surveys. Throughout the work was an emphasis on assessing social inequality in transit service provision.

The work also provided some novel empirical findings regarding temporal fluctuations in transit-based accessibility and social equity in service provision. A brief summary of the newly created analytical possibilities and empirical findings follows.

First, temporal trends in transit connectivity were examined by aggregating over the entire cube. This allowed me to detect the major temporal trends in the system such as the start and end times of the network, as well as peak hour boosts in service. While the results here were seldom surprising, and probably not worth the computational burden associated with creating the cube, the ability to summarize transit schedules in a standardized way for agencies around the world was one promising aspect of this approach.

Examining the spatial patterns, it was noticed that for the travel times, the biggest differences between days were occurring in the northern and southern portions of the study area, with these areas having much higher travel times on the weekends compared to the weekdays. However, as mentioned, this could be the result of the geographic distance issue and the fact that most of the origins/destinations are located in the center of the study area. Exploring the travel speed variations across the different days helped to correct for this by now showing that the areas in the northern and southern portions were actually faster travel speed wise thanks in large part to FrontRunner service. In addition, in the center of the valley the areas around TRAX or FrontRunner locations were shown to also have these better travel times. Therefore, examining travel speed was crucial to this research.

Lastly, how the Euclidean, vertical, and horizontal distance affected travel times was explored. It was determined that obviously distance plays an important factor in travel times, but that horizontal distance resulted in higher travel times compared to vertical distance due to the orientation of the network's infrastructure that has TRAX and FrontRunner providing better service north and south.

The cube also allowed this research to be able to examine how the travel times and travel speeds fluctuated from all origins to destinations, as well as from specific origins to specific destinations. Using supplemental information about the social groups of the origins in the study area, the cube could be utilized to examine social inequality to different types of locations. It was noticed that similar trends are noticed for all destinations, especially in regards to times when service is the best or service is the worst. The lowest travel times for most destinations tended to be during early morning around 6 or 7am, and then again around 3–5pm in the afternoon. By contrast, the higher travel times tended to be present midday. However, the extent of fluctuation between what was considered good or poor depends on the location. Some locations only had about 5 to 10 minute differences between what was considered the best or poorest service throughout the day, while others had closer to 20–30 minute differences as a result of intense fluctuations. Travel speeds also tended to show this trend, with higher travel speeds in the early morning and late afternoon and lower travel speeds around 11am–1pm.

Similar to when exploring travel times and speeds for all origins to specific destinations, similar findings were found when examining specific origins to specific destinations, with travel times being lower and travel speeds being higher in the early morning and late afternoon. However, when exploring the minute-by-minute graphs, as well as the graphs showing how the ranges fluctuated, it was seen that some OD pairs were provided fairly consistent service throughout the day with not much change in travel times or speeds, while others, such as the Salt Lake International Airport to University of Utah, noticed a lot of fluctuations in travel times and speeds throughout the day.

When exploring the equality between the different variables in each of the sociodemographic groups of interest, it was seen that overall there was a similar trend of inequality, such as those under the age of 18 consistently having higher travel times than those over 18. Examining the travel speeds helped to highlight the inequality much better though. While the differences in travel times between the different variables were fairly large, when comparing the travel speeds it was noticed that the same differences still existed but to a lesser extent. This helped to highlight why looking at travel speeds was an important component in examining transit accessibility due to the influence that geographic distance could have on travel time results.

Travel surveys allowed for a better understanding of equality by examining the level of service that was being provided for the different sociodemographic groups based on the times that they actually took trips. This particular approach allowed for a more complete picture, being able to discuss the similar types of inequalities witnessed between two separate travel surveys, such as both of the surveys indicating that older individuals, as well as individuals from households with high incomes, tend to be provided better service than those that are younger or less affluent, respectively.

In addition to the new empirical findings listed above, this thesis has led to the creation of a new set of software tools to be used in future accessibility studies. These tools could be used to create newer versions of the cube as changes are made to the transit network in order to determine if certain areas or social groups are provided better, worse, or equal levels of access after changes are made to a transit network. The hope is that as computational capabilities improve, this tool will be able to create newer versions of the cube in hours instead of days so that real-time change analysis can be performed. The tools created for this project also allowed for me to easily extract data from the cube as needed. While the entire cube, as has been demonstrated in this paper, might not be needed for an overall view of a transit network, its creation allows for researchers and planners to extract data as the need arises, such as if they are interested in the travel times or travel speeds to different hospitals or employment locations or educational centers. In addition to extracting the data, these tools also automatically performed statistical analyses on the data that were extracted in order to give the researcher or planner a better understanding of that particular subset of data, such as the average travel time or travel speed across the different minutes, hours, or days. As a result, these tools provide a new direction for transit and accessibility analysis in the discipline of transport geography and GIS. While most of the previous transit and accessibility studies have focused mainly on fixed analyses of accessibility, this research helps provide the framework and background into how dynamic accessibility analyses are more appropriate than the predecessors, and it can be used to gain a better understanding in the dynamics of the modern day public transit networks.

While the work contained in this thesis was quite innovative, the public transit travel time cube was a new discovery and suffered from some shortcomings such as the understandings of how it might be used still being a work in progress. However, the analyses performed in this research were a good preliminary review of how the cube could be helpful in determining the fluctuations of a transit network over the different days of the week, especially to specific destinations of interest and also between origin/destination pairs that are of interest. In addition, while the current configuration of the tool that calculated the travel time results, as well as software and hardware restrictions, resulted in slow processing times, future updates to the tool and software/hardware advances would hopefully allow for the tool to be run in hours instead of days. In addition, more detailed planning analyses could be performed, by perhaps using land parcels as origins and destinations (if social data are not required) instead of CBGs. More detailed and faster processing would allow for easier planning by being able to adjust the schedule and run the tool fairly quickly, seeing the consequences of the schedule adjustment, and being able to fine-tune the schedule without having to implement it first.

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